PREDICTORS OF SUCCESS FOR COMMUNITY COLLEGE DEVELOPMENTAL MATHEMATICS STUDENTS IN ONLINE, HYBRID, AND TRADITIONAL COURSES

A Dissertation
by
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ABSTRACT

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The recent growth of the internet has had a large impact on education and caused a growing demand for online courses. There has also been a demand for hybrid courses, which offer a compromise between the flexibility of online courses and the personal interaction of seated courses. Online and hybrid courses provide new educational opportunities for students who are unable to attend traditional classes because of conflicts due to work and family responsibilities. This is particularly true of community college students, who are often nontraditional adult learners. A significant number of these students face the additional obstacle of arriving unprepared for college level classes. In the United States, over half of the students in community colleges take one or more developmental courses to prepare themselves for credit-bearing classes in their program. The largest segment of developmental education is developmental mathematics. Developmental students start out behind their peers; the flexibility of online or hybrid classes can provide a way to help them catch up. Unfortunately, there is very little research on the relationship between the unique characteristics of community college developmental math students and their ability to succeed in online and hybrid courses.

The problem addressed by this study is the need to identify practical predictors of success for community college developmental mathematics students in online, hybrid and seated course delivery formats. This study examined two possible predictors of success, mathematics self-efficacy and technology self-efficacy, in the three delivery formats and how they related to performance on a final assessment.

The study used a quantitative research design employing binomial logistic regression to determine if the independent variables (math self-efficacy and technology self-efficacy) were significant in predicting the outcome category (score on the final assessment dichotomized about the mean). Next linear regression analysis was used to build a predictor equation for a particular score on the outcome variable. A previously developed survey and an adapted version of another survey were combined to measure the independent variables; demographic factors were also measured for descriptive purposes.

Binomial logistic regression analysis showed that math self-efficacy was a valid predictor of success for the developmental math students in this study but technology self-efficacy was not. Regression analysis produced a valid equation to predict standard score from average math self-efficacy score. When separated into groups according to course format, math self-efficacy was only a valid predictor for students in hybrid courses. The implications of these results are discussed and recommendations are made for further research.

DEDICATION

This work is dedicated to my family: my wife Vicki; my children George, Heather, and Michael; my son-in-law Andy; and my grandchildren Katie, Emma, Nathan, Ian, Zack, Jemma, and Ella. Each of you inspires me to be all I can be.

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CHAPTER 1: INTRODUCTION

In the United States, over half of the students in community colleges take one or more developmental courses to prepare themselves for credit-bearing classes in their program (Bailey, 2009; Bailey, Jeong, & Cho, 2010a; Perez & Foshay, 2002). Among these students, the greatest number need further preparation in mathematics to successfully achieve their educational and career goals (Bailey, Jeong, & Cho, 2010b). To meet this need, colleges offer developmental mathematics classes and student support services. Traditional lecture courses employ a delivery format students have already experienced to repeat mathematical content students have failed to master; these strategies have not been highly successful with developmental students (Boylan, Bonham, & White, 1999). Colleges are seeking alternative strategies that promote active learning and increase students' chances of success. Computers and the internet have the potential to deliver learning in a way that actively involves students and that offers flexibility to busy adult learners. However, questions have arisen about whether developmental students are likely to succeed in an online or hybrid seated/online environment (Boylan, 2002). Because these delivery formats will benefit some students, colleges need a practical way to reliably predict which students are likely to be successful in an environment that relies on computers to deliver some or all of the course content. This study addresses that need by examining two potential predictors of success for developmental mathematics students in online, hybrid, and traditional course delivery formats.

Statement of the Problem

The recent growth of the internet has had a large impact on education. Online enrollment in postsecondary colleges and universities increased 16.9% during the fall semester of 2008 despite only a 1.2% growth in total enrollment (Picciano, Seaman, & Allen, 2010). Clearly there is a growing demand for online courses. In the United States, 97% of community colleges offer courses in an online format (Parsad & Lewis, 2008). Online courses have almost completely replaced other distance education methods (such as correspondence courses and video broadcasts) and have become the primary method of delivering distance education in higher education (Meyer, 2002). Allen and Seaman (2008) report that 70.7% of postsecondary educators see online education as a critical part of their long-term strategy.

Online courses provide new educational opportunities for students who are unable to attend traditional classes because of conflicts due to work and family responsibilities. This is particularly true of community college students (Lim, 2001), who are often nontraditional adult learners; these students are attracted to the flexibility and convenience online courses provide (Allen & Seaman, 2008). A significant number of community colleges students face the additional obstacle of arriving unprepared for college level classes. In the United States, over 50% of the students in community colleges take one or more developmental courses (Bailey, 2009; Bailey et al., 2010a; Perez & Foshay, 2002). Developmental students start out behind their peers; the flexibility of online or hybrid classes can provide a way to help them catch up. However, there is very little research on the relationship between the unique characteristics of community college students and their ability to succeed in online courses (Jones, 2010). There is even less research in this area focused on developmental mathematics students; this study addresses that gap in the literature.

The educational effectiveness of online learning in higher education should be at least equal to that of a traditional classroom environment (Rovai & Baker, 2005). However, there are concerns about whether or not this is true (Noble, 2002). Russell (2001) surveyed the existing research and reported no significant difference in outcomes between the two delivery methods. However, Merisotis and Phipps (2000) observed design flaws in popular research methods and declared research about differences in the two methods to be inconclusive. A recent meta-analysis by the U.S. Department of Education (Means, Toyama, Murphy, Bakie, & Jones, 2009) found online students in higher education actually had slightly better learning outcomes than students in seated courses. On the other hand, a study by Jaggars and Xu found online community college students were less likely to complete courses than their counterparts in seated classes (Brown, 2011).

Among community college students, developmental students face unique challenges when it comes to online learning. Boylan (2002) recommends technology be used in moderation with these students. He goes on to say, “Computer-based distance learning has yet to be proven effective with developmental students. Distance learning often requires independent learning skills, study discipline, time management skills, and a high degree of motivation. These characteristics are not plentiful among developmental students (p. 82).” While this may be true of developmental students in general, some will have the skills and motivation to succeed or even prosper in online or hybrid courses; the challenge is to identify these students.

Hybrid courses offer a compromise between the flexibility of online courses and the personal interaction of seated courses while retaining many of the benefits of both formats. Typically hybrid courses are scheduled so that students meet in a classroom for 50% of class time and independently use computers and the internet to practice and complete assignments for the other half of the class time. This strategy of delivering content through lecture and supplementing it with computer activities is commonly called computer-assisted instruction (CAI). An extensive review of studies on CAI math courses in higher education by the U.S. Department of Education (2005) found CAI courses had higher, lower, or no difference in pass rate, no difference or higher rates of persistence, and no difference in final grades compared to traditional seated courses. The authors concluded that offering courses in a variety of formats allows students more freedom to choose a delivery method that best suits their own learning style.

In summary, the problem is the need to identify practical predictors of success for community college developmental mathematics students in online, hybrid, and seated course delivery formats. This study addresses that need by examining two possible predictors of success in the three delivery formats and how they relate to performance on a common final assessment. The results provide insight into technological and mathematical indicators that may affect the success of developmental students. The goal is to provide data that will help community college administrators, faculty, and students determine a student's probability of academic achievement and success in an online or hybrid class.

Purpose of the Study

The purpose of this study was to test theories that relate mathematics self-efficacy and technology self-efficacy to student achievement for developmental math students at a large suburban community college. The independent variable of mathematics self-efficacy was defined as a student's belief in his or her own ability to successfully perform mathematical tasks (Hackett & Betz, 1989). The independent variable of technology self-efficacy was defined as a student's belief in his or her ability to use computers and to learn new computer skills (Lim, 2001). The dependent variable of student achievement was defined as the results on a common comprehensive final exam in two levels of developmental mathematics classes.

The following research questions guided the study:

1. To what extent does course-specific mathematics self-efficacy predict performance on a final assessment in a developmental math course?
2. To what extent does technology self-efficacy predict performance on a final assessment in a developmental math course?
3. Do these predictors of success differ among online, hybrid, and traditional face-to-face courses?

Significance of the Study

According to the North Carolina Community College System (NCCCS, 2010), the number of students enrolled in one or more online courses increased by 29% in 2007-08 and by 24% in 2008-09. The number of students enrolled only in traditional classes decreased by 4.0% in 2007-08 and by 4.6% in 2008-09. Clearly there is an increasing demand for online classes and many new students are selecting online courses rather than only seated courses. Colleges are responding by creating more online courses.

In 2009, NCCCS President Scott Ralls established the North Carolina Developmental Educational Initiative (DEI). The first task for DEI was to redesign developmental math. The current series of three one-semester courses will be replaced by eight shorter modules focused on specific math competencies. Standardized placement testing will be replaced with diagnostic tests to determine which competencies students need to develop. The new design is being piloted in spring 2012 and will be fully implemented across the state in fall 2012 (NCCCS, 2011). Individual colleges will be given the choice of how to deploy the new design, whether in a seated, online, or some hybrid form. With the growing popularity of online courses, colleges will find online or hybrid courses an attractive way to deliver the new modules. This study provides valuable information about predictors of success for developmental math students that will help inform these decisions. This is true not only for North Carolina but for other states adopting a modular approach to developmental math or exploring new ways to deliver these courses.

Developmental math faculty may be able to use valid predictors of success found in this study to help identify students who are and are not likely to succeed in developmental math and advise them properly. They may also be able to identify students who are at risk for not successfully completing developmental math courses. This will enable faculty to provide better advice about the most suitable format for these students or possibly provide them with additional technology or math resources that should increase their chances of success.

Community college administrators may benefit from this study by obtaining data that allow them to set policies about requirements for enrollment in online or hybrid developmental math courses. Measurement of critical factors for success identified by this study could be made part of existing placement procedures, or additional assessments could be developed and used when students wish to enroll in online or hybrid developmental mathematics classes. Such screening could help avoid dropouts and failures that can damage an institution's reputation in the community or even place accreditation in jeopardy; it will also help the institution support student success.

Students may benefit from this study by learning what characteristics they need to be successful in online or hybrid courses. They may decide traditional courses are a better fit for their particular learning style. If they choose to enroll in an online or hybrid course, they will be aware of areas where they may need to seek additional help or resources.

Developmental educators and researchers may benefit from this study. There is very little literature examining what factors predict success for community college students in online courses. There is even less focused on developmental mathematics students. This study seeks to fill that gap in the literature.

Meaning of the Issue for the Researcher

The researcher has been a community college educator for over 12 years, serving as an instructor, a department chair, and most recently as an associate dean in engineering and industrial technology programs. Most of his students are required to take one or more developmental math courses before entering their program of study. In some cases this has caused them delays in graduation and hardships due to loss of government funding because they exceeded time limits for program completion. The DEI math redesign offers the possibility of streamlining and focusing the developmental math education process to allow students to minimize the potential negative consequences of placing into developmental math. By studying predictors of success for developmental math students in the various formats, this study can provide colleges with data that will help them make decisions about the formats they will use for the new modules, as well as with practical tools for predicting student success. The goal is to help optimize the process for all North Carolina community college students who need developmental math, especially those the researcher works with each day.

Definitions

Many terms used in this study are common to community college, developmental mathematics, and online/computer-assisted education settings; the terms defined here provide clarification where ambiguity might exist.

Asynchronous: Students and the teacher do not have personal interaction at the same time or place (Phipps & Merisotis, 1999).

Computer-assisted instruction (CAI): Tutorials, drills, graded assignments, homework, quizzes, examinations, and other activities delivered by a computer as a supplement to teacher-directed instruction.

Demographics: For purposes of this study, demographics are defined as age, gender, race, marital status, employment status, having dependents, student enrollment status, and previous experience with online and developmental math courses.

Developmental Mathematics: Courses and support services designed to provide the knowledge and skills underprepared students need to succeed in college-level mathematics courses.

Distance/online education or Distance/online learning: The teacher and students are physically separated; the majority of course content is delivered via computers and the internet. For this study, online instruction is delivered asynchronously via the Course Compass learning management system and interaction between the instructor and students is typically limited to electronic mail and discussion boards.

Full-time student: Students who are enrolled in 12 or more semester hours during a 16-week semester are considered full-time.

Hybrid Course: A hybrid course uses a combination of seated lecture sessions and online computer work. For the purpose of this study, a hybrid course meets in person for 50% of the total class time; students are assigned online computer work for the remaining half of the time.

Mathematics self-efficacy (MSE): A student's belief in his or her own ability to successfully perform mathematical tasks (Hackett & Betz, 1989).

Part-time student: Students who are enrolled in less than 12 semester hours during a 16-week semester are considered part-time.

Technology self-efficacy (TSE): A student's belief in her or his own ability to use computers and learn new computer skills (Lim, 2001).

Traditional (or seated) lecture course: This type of course meets face-to-face in a classroom during scheduled days and times for the entirety of the class hours. Content is delivered primarily through lecture, although group work may occur and computers/software may be available as an outside resource.

Organization of this Paper

This chapter introduced the issues relating to community college developmental math student success and the need for additional studies focusing on the unique characteristics of these students. In light of the growing demand for course delivery methods that include an online component, community college administrators and faculty require more information to enable them to help developmental students be successful in each format. Students need to be informed of the characteristics which will allow them to be successful in courses using various delivery methods.

Chapter 2 examines the literature relating to success factors for developmental mathematics in hybrid, online, and traditional courses. The chapter begins with an examination of developmental math then focuses on the independent variables for this study, mathematics self-efficacy and technology self-efficacy. The subsequent sections include a review of the research on the various delivery formats and establish a conceptual framework for the study. Chapter 3 provides an explanation of the methodology used in the study. Chapter 4 reports the findings of the data analysis as well as descriptive statistics. Chapter 5 includes a summary of the findings, conclusions, and recommendations for further research.

CHAPTER 2: REVIEW OF THE LITERATURE

More than half of new students who arrive at community colleges need to further develop their mathematical skills before enrolling in college-level mathematics courses in order to pursue their educational and career goals (Bailey et al., 2010a). According to Maxwell (1979) and Casazza (1999), there always have been and always will be college students who are underprepared and academically weak but who are quite capable of achieving success with additional assistance. Developmental mathematics provides this assistance through courses and services designed to prepare students for college-level work. A study by the National Center for Education Studies (2003b) found that 99% of two-year colleges offered at least one developmental math course in Fall 2000. Nationally, around half of the students entering community college require developmental work (Bailey, 2009; Bailey et al., 2010a; Kirst & Venezia, 2001). Educators are concerned about the best way to meet the diverse needs of developmental students. Considerable research has established best practices and policies for developmental education (Boroch et al., 2010; Boylan, 2002; Edgecombe, 2011; Hadora, 2011; Perin, 2011). However, there has been limited research on the effects of online or hybrid instruction on the success of community college developmental math students.

This literature review begins with the definition and a brief historical overview of developmental mathematics. Two potential predictors of academic achievement and success for developmental math students, mathematics self-efficacy and technology self-efficacy, are then considered along with the rationale for why these predictors were chosen as the focus in this study. Next is an examination of three methods of developmental math course delivery used by many community colleges: traditional seated, hybrid, and online distance learning. A conceptual framework derived from themes in the literature is then constructed. The review concludes with a discussion of what implications for this study arise from the literature reviewed.

Definition of Developmental Mathematics

Developmental mathematics is one component of the field of developmental education. The National Association for Developmental Education (NADE) gives the following definition for the larger field:

> Developmental education is a field of practice and research within higher education with a theoretical foundation in developmental psychology and learning theory. It promotes cognitive and affective growth of all postsecondary learners, at all levels of the learning continuum. Developmental education is sensitive and responsive to individual differences and special needs among learners. Developmental education programs and services commonly address academic preparedness, diagnostic assessment and placement, development of general and discipline-specific learning strategies, and affective barriers to learning. Developmental education includes but is not limited to: all forms of learning assistance, such as tutoring, mentoring, and supplemental instruction; personal, academic, and career counseling; academic advisement; and coursework (2011, p. 1).

The goal of developmental education, according to the motto of NADE, is to help “underprepared students prepare, prepared students advance, and advanced students excel” (Boylan, 2002, p.3). The most visible component of developmental education is a sequence of courses in reading, English, and math designed to prepare students for college-level work. Typically these courses do not carry college credit and are numbered below 100 (e.g., Mathematics 080). Other courses offered as part of developmental education include those that teach topics such as study skills, critical thinking, and learning strategies; these courses usually receive college credit and have titles such as “Freshman Seminar” (Boylan & Bonham, 2007). Some programs prefer to integrate these skills into the developmental courses. Another important component of a quality developmental education program is a range of support services such as advising, tutoring, and learning labs. Comprehensive services have been identified as a critical component in a successful developmental education program (Boylan, 2002). Many schools aggregate these services in learning centers.

Unfortunately, the students who need these additional services most are least likely to use them (Pettitt, 2006). Exactly what is considered developmental or remedial education differs somewhat among different institutions.

The use of the terms *remedial* and *developmental* is a matter of some confusion. Some educators still use the terms interchangeably while others make a distinction. Arendale (2005) reports *remedial education* was a term used from the 1860s through the 1960s which focused on cognitive skill deficits. Developmental education arose in the early 1970s and is much more comprehensive, as the NADE definition above shows. The term *remedial* has a somewhat negative connotation because it is used to describe weaknesses or deficiencies (Casazza, 1999). The implication is students are “broken” and in need of a “remedy” to fix them. On the other hand, the term *developmental* carries the positive connotation that through the use of well-designed courses, strategies, and services students can develop into individuals who are capable of achieving their educational and career goals. Over the years, the term *developmental* has largely replaced *remedial*, though the latter term occurs frequently in the early literature and has not disappeared from current literature.

Developmental Education/Mathematics: A Brief Historical Overview

Developmental education has always been a part of higher education in the United States. As early as the 17th century, Harvard University provided tutors for students who were found to be underprepared in Latin and Greek (Merisotis & Phipps, 2000). Land-grant colleges, established in the middle of the 19th century, offered programs for students who needed improvement in reading, writing, and mathematics. In the early 20th century, over half of all new students at Harvard, Yale, Princeton, and Columbia were required to take remedial courses. After World War II, the G.I. Bill brought an influx of veterans into higher education; many of these non-traditional students required remedial work. The Civil Rights Act of 1964 opened the college doors to many who would not have been able to attend otherwise, but who also required preparatory pre-college courses.

The growing need to prepare a significant number of students for college-level work called for a more formalized structure in developmental education. The 1960s saw the initial establishment of learning assistance centers and the movement to greatly expand the number of community colleges (Trenholm, 2006). Learning centers provided the services students needed to succeed and began the transition from remedial education to truly developmental education. Community colleges were open admission institutions designed to make higher education accessible to many first-generation students who could not attend university due to distance and cost (Cohen & Brawer, 2003); because they serve a diverse population, developmental education has always been an important part of the community college mission.

In the late 1960s developmental/remedial education began to be recognized as a field of study. Much of the earliest research was conducted by John Roueche and his colleagues at the University of Texas. They found that most remedial courses being offered were merely diluted versions of college-level courses; they also found the courses were poorly planned, poorly delivered, ineffective, and were rarely evaluated (Roueche & Kirk, 1974).

While some scholars began to focus on developmental/remedial education, they did so in a difficult climate. Boylan and Bonham (2007) note that in the mid-1970s, if legislators talked about developmental educational at all they discussed how to eliminate it or relegate it to the community colleges. There was little support for the field from legislators or the public, and little media attention. In 1977 the only journal dedicated to developmental/remedial education was the *Journal of College Reading and Learning*, which was published by the Western College Reading Association (now known as the College Reading and Learning Association). In 1976, what would later become known as the National Association for Developmental Education (NADE) was established. In 1978, the first issue of the *Journal for Developmental and Remedial Education* (now known as the *Journal for Developmental Education*) was published by the National Center for Developmental Education.

A major step in gaining recognition for the field occurred in 1984 when the National Center for Education Statistics (NCES) published a report on developmental education. This was a milestone because it was the first time the U.S. Department of Education acknowledged that developmental/remedial education was significant enough to merit research (Boylan & Bonham, 2007). NCES published subsequent studies on developmental education in 1990, 1996 and 2003. NCDE has also published two important national studies, one including 6000 randomly selected students from 160 colleges and universities (Boylan, Bliss, & Bonham, 1997) and another focusing on community colleges (Gerlaugh, Thompson, Boylan, & Davis, 2007). The Community College Research Center (2011) has also contributed a great deal of research focused on developmental education at community colleges. The field has prospered over the years; many journals, conferences, and professional organizations now exist.

Research has shown a consistent need for developmental education, although figures tend to vary due to differing ideas of what exactly constitutes this type of education (Merisotis & Phipps, 2000). McCabe (2000) reported only 42% of high school graduates were prepared for college work. Perez and Foshay (2002) reported a similar number, stating about half of new students at community colleges require developmental work. The NCES study on remedial education (2003b) reported that 71% of four-year institutions and 99% of two-year institutions offered at least one remedial mathematics course in the fall of 2000, and almost 22% of incoming freshmen enrolled in one of these courses. Reviewing the four national NCES reports, Boylan and Bonham (2007) found about 30% of freshmen require one or more developmental courses. Later studies focused on community colleges (Bailey, 2009; Bailey et al., 2010a) report more than 50% of new community college students require developmental coursework. Bailey (2009) also points out that since many students who place into developmental courses never enroll, the actual number of underprepared students is higher than the data show.

There is much research showing developmental education has been successful in increasing student achievement and retention (Boylan et al., 1997; Roueche & Roueche, 1993; Thomas & Higbee, 1996; Waycaster, 2001). Lesik (2006) showed that students who took developmental math had a much higher chance of successfully completing a college-level math course on the first try than those who elected not to do so. Comparing developmental students to other students, Boylan (1999) found that 22% of students who enroll at a community college complete an associate's degree while

24% of developmental students do so. At the university level, 46% of students complete a bachelor's degree compared to 40% of developmental students.

Bahr (2008) conducted a study of California community college developmental mathematics students to compare their academic attainment to that of students who began at college-level math. Despite the important policy implications of the efficacy of developmental math, he found previous studies on the topic were limited in scope or flawed. He studied eight years of longitudinal data on 85,894 freshmen at 107 colleges who first enrolled in 1995; academic achievement was measured by either attainment of a degree or certificate or transfer to a four-year institution. Using hierarchical multinomial logistic regression, he found the two groups were virtually indistinguishable in terms of academic attainment. This research indicates students who arrive at college needing developmental work in mathematics and who complete the developmental sequence achieve the same amount of success in higher education as those who do not.

The effectiveness of a developmental education program is directly related to how closely it follows best practices based on solid research. Boylan (2002) provided a detailed report on best institutional practices, program components, and instructional practices based on an extensive study by the Continuous Quality Improvement Network and the American Productivity and Quality Center in collaboration with the National Center for Developmental Education. Beginning with almost 60 institutions with a high reputation for quality developmental education, the study identified five exemplary programs for detailed study. In a later study, Boroch et al. (2010) conducted an extensive literature review to identify best practices as part of the Basic Skills Initiative for California community colleges. Their findings echo those of Boylan. Both books offer assessment tools to allow institutions to evaluate their developmental education programs.

Of the academic disciplines encompassed by developmental education, students consistently demonstrate the greatest need in mathematics; this is true both in four-year institutions (Duranczyk & Higbee, 2006) and in community colleges (Bailey, Jeong, & Cho, 2010b). In fall of 2000, 14% of college freshmen enrolled in developmental English courses while 22% enrolled in developmental mathematics courses (Parsad & Lewis, 2003). The ACT benchmark results for 2010 show even more disparity in test-takers who did not meet college-level benchmark scores: 34% for English, 48% for reading, and 57% for math (ACT, 2010). Bailey et al. (2010a) found that among community college students in the national Achieve the Dream study, 51% required one or more levels of developmental math while only 39% required developmental reading.

There are many reasons so many students arrive at college underprepared in mathematics. Often there is a poor alignment between what high schools teach and what colleges expect incoming student to know (Boylan et al., 1999; Hall & Ponton, 2005). Students may have failed to retain past learning because they experienced inefficient teaching practices that emphasized memorizing mathematical rules without creating understanding or showing applications (Hammerman & Goldberg, 2003). Adult students returning to college several years after high school often need to review past mathematical learning (Merisotis & Phipps, 2000). Some students struggle with math because they lack sufficient study, organizational or self-assessment skills (Hall & Ponton, 2005). Negative experiences in previous math classes cause some students to approach math with low confidence, poor motivation, and high math anxiety (Betz, 1978; Hammerman & Goldberg, 2003).

For whatever reason they need developmental math, achieving mathematical competence is necessary for students to meet their educational and career goals. There is a growing need for the ability to understand and use mathematics in the workplace; those with this ability will have "enhanced opportunities and options for shaping their futures" (National Council of Teachers of Mathematics, 2000, p. 1). Success in mathematics influences students' choice of major or even their ability to graduate (Hall & Ponton, 2005). Because almost all programs require students to pass a course in college-level mathematics, underprepared students are unlikely to achieve their educational and career goals unless they successfully complete developmental mathematics. McCabe (2000) predicted over 80% of new jobs would require a college education, and would call for higher levels of productivity, problem solving skills, and competence than existing jobs. Higher education, he says, must offer effective developmental education programs to allow underprepared students to achieve their educational goals and qualify for meaningful employment.

Predictors of Success for Developmental Mathematics Students

Past studies (Gupta, Harris, & Nellie, 2006; Hailikari, Nevgi, & Komulainen, 2008; Higbee & Thomas, 1999; Waycaster, 2004) have measured several characteristics of developmental students in order to predict success in outcomes such as academic achievement, retention, persistence, and graduation rates. The challenge is to find a set of possible predictors that are measurable, comprehensive enough to give an accurate assessment of potential success, and practical enough to be used to assess prospective students if institutions wish to do so. This section first provides an overview of the factors that have been used to predict student success in mathematics and online environments, particularly academic achievement. It then provides a rationale for choosing a relevant set of predictors that meet the criteria above. Finally, it examines studies which have used the predictors chosen for this study: mathematics self-efficacy and technology self-efficacy. Salient studies are those which focus on community college students, developmental students, mathematics students, and online or computer-assisted students; when they exist, studies that combine these foci are featured.

Higbee and Thomas (1999) reviewed the literature and reported several affective variables that have been identified as factors in the study of mathematics achievement: academic self-concept, attitudes toward success in mathematics, confidence in ability to learn mathematics, math anxiety, test anxiety, beliefs in the usefulness of mathematics, motivation, self-esteem, and locus of control. Cognitive factors that have been used include learning styles, visual/spatial ability, use of cognitive strategies, critical thinking skills, and past academic performance.

Focusing on predicting success in community college developmental math, Waycaster (2004) found the environmental factor of course site (on or off campus), the cognitive factors of placement test score and grade point average, and the demographic factor of age to be significant predictors of final grade in two levels of developmental math courses. A study focused on predictors of success for students in entry-level undergraduate university math courses (Gupta et al., 2006) found several factors to be significant. These included the environmental factors of course site, number of classes per week, number of 100-level courses completed, number of tutoring hours per week, instructor rank (full-time, part-time, or graduate student), and class size. Significant demographic factors included number of children, attendance, and age. Math attitude, an affective factor, was also found to be significant. Another study of predictors of achievement for university mathematics students (Hailikari et al., 2008) found significant variables to be the affective factor of academic self-beliefs and the cognitive factors of domain-specific prior knowledge and prior study success.

Undoubtedly, academic achievement for developmental math students is a complex issue affected by a multitude of potential factors. In order to focus this literature review, it is necessary to reduce the list to a minimum number of practical predictors that allow a valid assessment. Because the focus is on developmental math students, it can be argued that students have already been sorted according to the cognitive factor of their scores on math placement tests. Besides this, if schools wish to use other cognitive factors such as high school mathematics grades to predict academic success, these data are already available to them in the students' records. Therefore, other predictors will be chosen from affective factors. As Bonham and Boylan point out, "The affective domain is frequently an untapped area in attempts to promote students' achievement and retention in developmental mathematics programs" (2011, p. 4). Focusing on affective factors will help achieve the balance in cognitive and affective factors inherent to developmental education as defined by NADE (2011).

Social cognitive theory, especially the concept of self-efficacy, provides a tool for selecting the best predictors from the list of affective factors reported in the studies mentioned above. Bandura (1977) defines self-efficacy as the perceived belief in one's capabilities to perform a specific behavior and achieve specific results. Bandura, Barbaranelli, Caprara, and Pastorelli (2001) showed that self-efficacy is highly related to commitment, motivation, perseverance, resilience, and locus of control; while distinct, self-efficacy provides a central construct to which these other constructs are likely to correspond. When applied to mathematics, self-efficacy captures or is related to Higbee and Thomas' factors of attitudes toward success in mathematics, confidence in ability to perform mathematics, motivation, and locus of control. Lee (2009) studied the distinctions between math self-efficacy (belief in the ability to perform a specific mathematical task), math self-concept (broader feelings about mathematical competence and self-worth) , and math anxiety (negative emotions associated with mathematics); he found the three constructs are distinguishable but very highly related. Thus, math self-efficacy also provides insight into the affective factors of academic self-concepts, math anxiety, test anxiety, and self-esteem.

The other dimension under study is the online component of the courses. Because self-efficacy must be analyzed for a specific task in order to be useful (Bandura, 1977), the factor of technology self-efficacy captures the same set of affective information regarding computer and internet use listed above for math self-efficacy. The two self-efficacy factors potentially provide a comprehensive yet practical set of predictors for achievement in developmental math courses using various delivery formats.

Technology Self-Efficacy

Miltiadou and Yu (2000) noted that many online students feel apprehensive about using computers and the internet; they may spend their time learning to use the technology and be distracted from course content. To provide educators with a tool to measure students' perceived self-efficacy with online technologies, they created and validated the Online Technologies Self-Efficacy Scale (OTSES). Wang and Newlin (2002) studied 122 distance education college students in several sections of an introductory psychology course and found a strong correlation between technology self-efficacy and success measured by final examination score. DeTure (2004) studied six online courses in a variety of subjects at a southeastern community college in fall 2002. A total of 73 students participated in the study which examined technology self-efficacy using the OTSES and cognitive styles using another instrument. Neither technology self-efficacy nor cognitive styles were found to be significant predictors of student success measured by final course grade. However, this may have been due to wide variations in final grades and differences in course delivery styles used by the various instructors.

Recent doctoral dissertations have studied technology self-efficacy as a predictor of student success. Chih-hsuan Wang (2010) studied 256 online university students by administering an online survey that measured motivation, learning strategies, technology self-efficacy (using the OTSES) and course satisfaction, along with a demographics questionnaire. Using structural equation modeling, he obtained a model that was a good fit among the independent variables and the outcome variable of final course grade. His model showed students with prior online learning experience had better learning strategies which led to higher motivation. Higher motivation increased technology self-efficacy and satisfaction with the course, which led to higher final grades.

Jones (2010) studied 368 community college students in online and seated sections of an introductory computer class. She measured demographics, motivation, and technology self-efficacy (using the OTSES) by administering an online survey. The outcome variable was the grade on a common final examination. Using correlation and stepwise multiple regression, she found that none of the independent variables were significant outcome predictors of success for students in seated courses. Demographic factors were not a significant predictor for online students, but motivation and technology self-efficacy were both significant predictors of success for online students. Upon a finer analysis, significant motivation factors were those that focused on students' confidence and belief in their abilities to do well; these describe task self-efficacy regarding the subject of the course.

Mathematics Self-Efficacy

The applicable task self-efficacy for developmental mathematics students is mathematics self-efficacy (MSE). Cooper and Robinson (1991) were among the first to study the relationship between mathematics self-efficacy and mathematics performance. In a study of 229 students at a public mid-western university, they measured MSE, math anxiety, math performance, perceived support from parents and teachers, and demographics. They found perceived support from parents and teachers had a small but statistically significant relationship to math self-efficacy, $r = .09$, $p < .05$.

They observed significant correlations between MSE and mathematics anxiety ($r = -.41$, $p < .001$) and MSE and performance ($r = .22$, $p < .001$). A limitation of their study, however, is that they took all the data, including performance data, concurrently. “When data are gathered simultaneously, the direction of causality or the spuriousness of the relationships cannot be determined” (Cooper & Robinson, 1991, p. 8).

Pajares and Miller (1995) conducted a study of 391 university mathematics students to explore Bandura’s (1986) assertions that self-efficacy must be measured for a specific task to provide useful insight. They measured mathematics problems self-efficacy (confidence in ability to successfully solve specific math problems), math-related tasks self-efficacy (confidence in ability to perform general math tasks), and math-related courses self-efficacy (confidence to be successful in a math course). Students were then asked to solve mathematics problems. Their perceived mathematics problems self-efficacy proved to be a more powerful predictor of their performance than the other two math self-efficacies. On the other hand, they found math-related courses self-efficacy to be the most powerful predictor of choosing math-related college majors. They concluded that “because judgments of self-efficacy are task specific, measures of self-efficacy should be tailored to the critical task being assessed and the domain of functioning being analyzed to increase prediction” (Pajares & Miller, 1995, p. 190). Their work supports Bandura’s (1989) theory that self-efficacy must be measured for a specific task to be useful in predicting success at that task.

Hall and Ponton (2005) conducted a study to measure differences in MSE between university students enrolled in a developmental math class (Intermediate Algebra) and a college-level class (Calculus I). They tested 185 freshmen at a southeastern four-year institution, 80 from Calculus I and 105 from Intermediate Algebra. They used the same instrument to measure MSE at both levels. After testing for and confirming a normal distribution of math self-efficacy scores, they conducted an independent *t*-test and found the mean MSE score for the Calculus I students, 7.08, was significantly different from the mean self-efficacy score for the developmental students, 5.33, with $t = 8.902$, $p < .001$. They concluded the calculus students had greater MSE than the developmental students and recommended developmental educators explore ways to foster math self-efficacy along with mathematical ability.

In research that combined many elements relevant to community college developmental math students using computer-aided instruction, Spence and Usher (2007) studied 164 students (88 traditional, 76 online) enrolled in a developmental intermediate algebra course at a two-year public college in the southeastern United States. The study had three goals: to determine if traditional and online students differ by age, motivational disposition, or mathematics achievement; to examine the degree to which course setting, age, and key motivational constructs predict level of engagement with mathematics courseware; and to determine the degree to which those key constructs along with mathematics self-efficacy and level of courseware engagement predict mathematics achievement. The key motivational constructs measured included computer self-efficacy using a subscale of the computer self-efficacy (CSE) scale (Murphy, Coover, & Owen, 1989), self-efficacy for regulated mathematics learning using a subscale adapted from the Children's Multidimensional Self-Efficacy Scales (Zimmerman, Bandura, & Martinez-Poins, 1992), and computer playfulness using a subscale of Webster and Martocchio's (1992) Computer Playfulness Scale (CPS). They found the two groups differed significantly in age, mathematics self-efficacy, computer self-efficacy, courseware engagement, computer playfulness, and mathematics achievement. When the results were controlled for age, all other differences remained. When results were controlled for mathematics self-efficacy, differences in achievement were no longer significant but other differences persisted. Regression analysis showed mathematics grade self-efficacy and age jointly predicted achievement. They concluded (a) mathematics self-efficacy is an important predictor of mathematics achievement, (b) computer self-efficacy and computer playfulness are related to courseware engagement, and (c) self-regulation is an important part of online learning.

Lee (2009) used international data from the 2003 Program for International Student Assessment (PISA), which collected data from more than 250,000 15-year-olds in 41 countries, to explore the factoral structure of three closely related constructs: math self-efficacy (belief in the ability to perform a specific mathematical task), math self-concept (broader feelings about mathematical competence and self-worth), and math anxiety (negative emotions associated with mathematics). The 2003 PISA focused on mathematics; several items on the survey instrument used in the study addressed each of these three factors. Using exploratory and confirmatory factor analysis, Lee determined the three constructs, although highly related, were distinguishable across the countries. Although the three constructs are moderately correlated to one another, his data show each appears to have an important but different contribution in predicting mathematical performance.

Kitsantas, Ware, and Cheema (2010) also used data from the 2003 PISA; their goal was to explore whether analytical method makes a difference when predicting mathematics achievement from mathematics self-efficacy. They used PISA data from 5,456 students from 274 high schools in the United States. They analyzed the data based on two models using regression methods at both student and school levels and also based on five different hierarchical linear models of the data. Their results show that regardless of the method of analysis, math self-efficacy is an important predictor of math achievement. This was true even after controlling for demographic characteristics.

Two recent doctoral dissertations have featured mathematics self-efficacy. Peters (2009) studied 15 algebra instructors and 326 students at 10 public universities to explore the relationship between classroom climate, mathematics self-efficacy, and mathematics achievement. She surveyed the instructors to obtain data on classroom climate and administered an instrument to the students to determine their mathematics self-efficacy. She obtained final examination scores for the students and used Item Score String Estimation to set the scores to a standard scale. Pearson's r methods suggested statistically significant correlations among classroom climate, mathematics self-efficacy, and mathematics achievement. Hierarchical linear modeling suggested mathematics self-efficacy had a direct effect on achievement and classroom climate had a direct influence on mathematics self-efficacy.

Kilian (2010) conducted a qualitative study in which she interviewed university students in a developmental math class at a four-year university and measured their mathematics self-efficacy. She found a strong relationship between academic success in the math class and self-efficacy. Successful participants displayed more confidence, competence, and effort while those who did not succeed exhibited stress and a lack of confidence in their ability.

Mathematics self-efficacy and technology self-efficacy are two important predictors of success for developmental mathematics students. Although there are many other factors, the literature shows these two used together should give a strong, centralized overview of potential achievement for developmental mathematics students in traditional, online, and hybrid course delivery formats. The next section of this literature review focuses on those three formats.

Course Delivery Formats

Traditional Course Delivery

Traditional courses are those in which 100% of the instruction time is scheduled in a classroom with the students and the instructor meeting face-to-face. Computers and software may be used as learning tools, but this takes place either outside of class hours or in a computer laboratory with the instructor present; computer activities are purely supplemental to classroom-based activities. For purposes of this study, traditional refers to the setting and the physical presence of students and the instructor rather than to traditional teaching methods, such as exclusive use of lecture. Thus, a traditional course delivery format may use either teacher-centered or learner-centered instructional strategies. However, research has shown that learner-centered strategies are much more effective for developmental students (Boroch et al., 2010; Boylan, 2002).

Boylan (2002) advocates several learner-centered instructional strategies that have proven to be successful for developmental students in his work on research-based best practices. These include the use of learning communities, Supplemental Instruction (in which students who have previously succeeded in a developmental course lead outside-of-class sessions for students currently taking the course), individualized instruction, peer reviews of student work, collaborative learning, computer-aided instruction, mastery learning, small group work, and other active learning techniques. He recommends these techniques be varied to accommodate the diversity of developmental students. He also recommends technology be used with moderation; the best programs in developmental education "recognize the limits as well as the strengths of technology and emphasize the importance of instruction delivered by faculty" (p. 82).

Boroch et al. (2010) repeat many of Boylan's recommendations for student-centered practices in developmental education, particularly the use of a variety of active learning techniques. They also offer several best practices specific to developmental mathematics; these include small-group instruction, problem-based learning, contextual learning, use of manipulatives, and use of technology. Additionally, they recommend that developmental math instructors address affective factors such as math anxiety.

Hybrid Course Delivery

Hybrid courses are those which meet face-to-face regularly but also deliver a significant portion of the instruction (typically 50%) through online distance learning methods using computers and the internet. Because this format uses computers to supplement face-to-face instruction, it is sometimes known as Computer-Assisted Instruction (CAI) (Spradlin, 2010). Students using CAI receive the benefits of regular interaction with the instructor and peers as well as the flexibility of pursuing the online portions of the class when it is convenient for them. CAI is potentially beneficial for developmental students for many reasons.

Many researchers have advocated providing developmental students a choice of instructional approaches. No single instructional method or course delivery format will meet the needs of all developmental mathematics students because they come from a variety of mathematical backgrounds and have diverse learning styles (Armington, 2003; Boroch et al., 2010; Boylan, 2002; Boylan et al., 1999; Higbee & Thomas, 1999; Roueche & Kirk, 1974; Waycaster, 2001). CAI provides many of the elements cited by Boylan (2002) and Boroch et al. (2010) as best instructional practices for developmental students. Computer-assisted instruction provides individualized instruction which allows students to focus on areas they need to develop instead of moving at the pace of the entire class. CAI provides instant feedback and frequent assessment. Computers may be programmed for mastery learning by not allowing students to progress to new material until they have mastered fundamental concepts. CAI is highly student-centered and provides several elements of active learning as the students interact with the computer media through means such as watching interactive videos, practicing problems related to new concepts, and using resources for deeper learning provided by the software.

Much of the software used in developmental mathematics was developed by textbook publishers (Kinney & Robertson, 2003). The software typically used in hybrid classes is designed to supplement a traditional course; the instructor provides the content and the software provides practice problems and illustrative videos. The instructor introduces new concepts during the seated portions of the course and the students review and practice those concepts during the online portions. Instructors can also create electronic homework and examinations that are graded and recorded by the software. This allows the students to receive immediate feedback on their progress in the course (Kinney & Robertson, 2003). Drill and practice features of the software provide exercises designed to build speed and accuracy in problem solving (Olusi, 2008). Tutorials provide interactive guided practice problems, promoting active learning. Some software can provide students with tailored study plans based on their homework and quiz scores (Hannafin & Foshay, 2008).

Online Course Delivery

Online courses are those which deliver 100% of the content through distance learning using computers and the internet. Interaction with the instructor and other students is generally limited to electronic mail and discussion boards. The newest form of course delivery, online learning has grown rapidly as the internet has become a major media source in U.S. society. From 1994 to 2001, the number of higher education institutions offering distance education increased from 33% to 55% and the number of students enrolled in online distance education increased from 753,640 to 3,077,000 (National Center for Education Studies, 2003a). Growth has continued; in the fall semester of 2007, postsecondary institutions saw a 16.9% growth rate in online enrollment compared to a 1.2% growth rate in total enrollment (Picciano et al., 2010). Clearly the demand for online courses is increasing. Parsad and Lewis (2008) report that 97% of U.S. community colleges offer online distance education.

Online courses use a student-centered model that allows students to work at their own pace, although lessons must be completed according to a schedule (Kinney & Robertson, 2003), and requires them to take responsibility for their own learning. The computer software provides a thorough explanation of content using interactive multimedia software. Student activities are embedded within the instruction, allowing students to try out new concepts as they learn them. The software provides immediate feedback on activities and detailed solutions. The courseware provides online assessments which are graded immediately (Kinney & Robertson, 2003). The instructor is available as a resource when students have difficulties; contact may be through email, threaded online discussion, telephone, or visits during office hours. Virtually all contact between students and the instructor is electronic, although many institutions require a face-to-face orientation session at the beginning of the semester and a seated, proctored final examination at the end (Armington, 2003).

However, research has shown online learning is not for everyone (Milligan & Buckenmeyer, 2008). Moore (1986) stated distance learners must be self-directed, have a conscious intent to learn, and be able to establish and complete goals. He noted that public schools often do not prepare students to be self-directed learners. Some students require continual face-to-face guidance to succeed. Maddux (2004) identified four characteristics of successful online learners: they are independent and motivated to learn; they enjoy independent work; they are skillful at time management; and they possess excellent written and verbal communication skills. Milligan and Buckenmeyer (2008) offer a 10-question assessment survey to assist in determining the readiness of students for online learning based on access to the internet, comfort with independent work, time management skills, and comfort with computers. However, these issues could easily be addressed by an advisor in discussion with the student without the use of a survey.

Computer Instruction and Developmental Mathematics

Computer-Assisted Instruction

Several studies have shown that developmental mathematics students using computer-assisted instruction perform at least as well as those receiving traditional instruction. Waycaster (2001) studied 15 developmental mathematics classes at five community colleges in Virginia using three modes of instruction: lecture, individualized instruction with tutoring, and computer-assisted instruction. She found no significant difference in pass rates among the groups. Kinney and Robertson (2003) studied developmental mathematics university students in two formats. The first was a lecture class with computer software available as an external, optional resource. The second format used the computer software to deliver course content; the software was designed for a distance education course but these students used it in a computer lab and met during scheduled hours with the instructor present. Students were allowed to work at their own pace but were required to attend class and complete examinations according to a schedule. There was no significant difference on the results of a common final examination between the lecture classes and the computer classes.

Villarreal (2003) reported the effects of changes to the method of delivering developmental algebra classes at a community college in Texas. The college was unhappy with pass rates in a format that used computers to deliver content in an open computer lab with tutors present. Many students lacked the self-discipline to complete the course; some students relied on the tutors to explain the material and did not use the computer tutorials. The course was unstructured and many students failed to manage their time well; they waited until the end of the semester and rushed to complete all the assignments before the deadline. The format of the courses was changed to three hours of lecture and three hours of computer lab per week. Pass rates increased 12% in two years. It should be noted that unlike Kinney and Robinson's concurrent study (2003), changes occurred over time at this community college. Differences in students and improvements in the quality of available software may account for differences in the two studies. Also, the lack of structure in the open lab format originally used by the Texas college is a significant difference from the structured computer lab format used by Kinney and Robinson.

Teal (2008) used a quasi-experimental pretest/posttest design to study differences between 152 community college developmental algebra students who received either computer aided instruction or traditional lecture. The CAI class met in a computer classroom and received short lectures with online lecture notes; the remainder of class time was used to do computer work or ask questions. Homework, quizzes, and tutorials were done on the computers. The traditional lecture students were instructed through lectures and were expected to take notes. They worked in groups, took quizzes and tests, and turned in homework together. Three instructors each taught one CAI class and one lecture class. The pretest to determine initial knowledge consisted of the results of a math placement test. Two posttests were used, a 16-question multiple choice test after six weeks and the standard department final exam at the end of the semester. The study showed no significant difference between scores for the two groups.

Spradlin (2010) did a quasi-experimental study comparing the academic performance of developmental math students in a seated environment to those in a hybrid CAI format. Participants came from six sections of a developmental intermediate algebra course in a large, private, eastern university; there were a total of 99 participants. She found no significant difference in final examination scores between the two groups.

While other studies have reported no significant difference in outcomes between CAI and seated delivery methods, Carol Twigg, president of the National Center for Academic Transformation (NCAT), reports dramatic improvements in outcomes and reductions in delivery costs for a CAI format known as the math emporium model (2011). Redesigns based on this model over the last 11 years have increased the percentage of students successfully completing developmental math courses by an average of 51% and reduced cost of instruction by an average of 30%. The underlying principle behind the emporium model is simple:

> Students learn math by doing math, not by listening to someone talk about doing math. Interactive computer software, personalized on-demand assistance, and mandatory student participation are the key elements of success (Twigg, 2011, p. 26).

Pioneered at Virginia Tech in 1998 as part of an NCAT project, math emporiums have since been employed at 37 universities and community colleges in both developmental and college-level math courses.

In the math emporium, students spend their course hours in a computer lab working with interactive math software such as ALEKS, Hawkes Learning System, or MyMathLab. Instructors and tutors are available to assist when students encounter difficulties. Some versions of the model require students to meet in the lab at scheduled times with an instructor present while others use an open lab format where students must log a minimum number of hours per week. Some versions also include a brief weekly group meeting to allow instructors to reinforce areas where testing has identified weaknesses.

The question arises as to why emporium models have been reported to be so successful when similar approaches have yielded either no significant difference between seated and CAI classes or poor results (Kinney & Robertson, 2003; Spradlin, 2010; Teal, 2008; Villarreal, 2003; Waycaster, 2001). Twigg (2011) attributed the following characteristics of redesign to the success, scalability, and sustainability of the emporium model: (a) whole-course redesign conducted by teams of faculty and administrators; (b) proven methods of integrating technology and learner-centered pedagogy; and (c) cost reduction as an integral part of the redesign. Critics of the emporium model say it greatly reduces human interaction, replaces a classroom environment of academic inquiry with raw information, and reduces instructors to mere tutors (Young, 2005). It should be noted that the reports of the success of the emporium model are mainly anecdotal and there is as of yet little published research data to support it.

Online Instruction

Englebrecht and Harding (2005) note that mathematical instruction presents a challenge in the online environment because mathematics is communicated with an extensive set of symbols that are not accommodated by the HyperText Markup Language commonly used on the internet. Newer software overcomes this problem by using Mathematical Markup Language or Java applets which allow a more extensive set of symbols. Because these technologies and the ability of web browsers to accommodate them are quite recent, mathematics has lagged behind other fields in online course development. Another difficulty they note is that because mathematics is highly conceptual in nature, both students and teachers have the perception that face-to-face contact is necessary to learn these concepts. Online mathematical learning requires a paradigm shift by both students and teachers.

Developmental educators have been reluctant to embrace online course delivery. The first National Study for Developmental Education in 1996 reported 3% of developmental courses were taught totally online; the second national study in 2007 found that number had increased only slightly (Gerlaugh et al., 2007). Boylan (2002) noted that distance education has not been shown to be effective with developmental students, who often lack the discipline, study skills, and motivation to be successful in a purely online environment.

Ford and Klicka (1998) compared four modes of courses delivery for two levels of developmental mathematics at a Pennsylvania community college. Courses in Fundamentals of Mathematics and in Basic Algebra were offered via traditional lecture, computer-assisted instruction without lecture, computer-assisted instruction with lecture, and online distance learning. In the Fundamentals course, no significant differences were found among the four modes in passing the course, passing the final exam, receiving an A or B on the final exam, remaining in college, or passing the next math course. In the Basic Algebra course, no significant differences were found between the four methods in passing the next math course, remaining in college, or passing the final with an A or B. However, computer-assisted and online sections had significantly higher final exam pass rates while traditional courses had higher course pass rates and course retention rates. The authors noted that students chose classes that fit their schedule without regard for computer content. They concluded that non-lecture formats are best suited for motivated, self-disciplined independent learners. As a result of the study, faculty decided to continue offering the various formats to meet the varied learning needs of students and to improve advisement to help students choose the right format for them.

In 1999 the League for Innovation in the Community College, PLATO Learning, Inc. and eight community colleges collaborated in an action research project to identify critical success factors for internet-based developmental mathematics courses (Perez & Foshay, 2002). The participants were 185 students from colleges in five states. The colleges had varying amounts of experience with internet-based learning and were encouraged to develop courses in various formats. Six colleges used the PLATO software to create online courses and two used it to supplement traditional courses. After implementing the new courses, data were gathered from instructors and students concerning perceptions and outcomes. The following were among the critical success factors identified by the study: easy internet access and courseware navigation; good technical support; courseware aligned to course objectives; individualized instruction; effective learner recruitment and counseling; mandatory orientation sessions; frequent contact between instructors and learners; availability of on-campus support services; high quality standards for content development; and support for the program from college leadership. Faculty reported the six best outcomes of online distance delivery were the following: software tutorial functions; time flexibility for busy adult learners; self-paced instruction; privacy for students; access to cutting edge technology; and interactive feedback.

Zavarella and Ignash (2009) studied developmental algebra students in lecture, computer-assisted non-lecture, and online distance learning sections at two campuses of a large urban community college in Florida to determine the effect of delivery mode on student retention. The completion rates were 80% for the lecture sections, 58% for the computer-assisted sections, and 61% for the online sections. They also found that students who chose a section for personal reasons, such as when the course was offered, were more likely to withdraw than those who chose a section based on their preferred learning style. The authors recommended that colleges carefully counsel students considering online classes and help the students choose a delivery format that is appropriate for them.

Xu and Jaggars (2011a) studied the effect of taking one's first college-level English or math course online. They used data from nearly 24,000 students in 23 community colleges from the Virginia Community College System from 2004 to 2008. Using multilevel logistic regression and compensating for differences within and across schools, they found a significant negative effect of taking the first introductory courses online. Students taking the first English course online were about twice as likely to fail to complete it as face-to-face students, and were about 65% as likely to receive a grade of C or better in the course. Those taking the first math course online were almost three times as likely to drop out as those who took the course face-to-face, and were only about 60% as likely to complete the course with a grade of C or better. They conclude that in key introductory courses in community colleges, online instruction may not be as effective as face-to-face instruction.

Xu and Jaggars (2011b) found similar results in a parallel study in Washington State. They tracked almost 51,000 community and technical college students taking courses in traditional face-to-face, hybrid, and online formats in a five-year study beginning in 2004. Controlling for student and course-level information, they found that students taking hybrid courses were equally as likely to succeed as traditional students. However, online students were more likely to fail or withdraw from courses compared to traditional students. Based on these studies, Jaggars commented, "an online course is not necessarily a desirable alternative to a face-to-face course for a developmental student" (Phillip, 2011, p. 1). This emphasizes the need to find reliable predictors of success for those developmental math students who will do well in an online course.

Conceptual Framework

The literature shows the topic of predictors of success for developmental math students in various course formats is a complex subject where many theories intersect. Two of the main theories that appear to be prominent in the literature are the self-efficacy aspect of social cognitive theory and online learning theory. This section will further examine these theories to show how they frame the logic of this study and suggest the chosen independent variables of technology self-efficacy and mathematics self-efficacy should be able to predict the dependent variable of academic achievement for developmental math students in seated, hybrid, and online delivery formats.

Self-Efficacy and Social Cognitive Theory

The most prominent theory for this study is based on the Social Cognitive Theory proposed by Albert Bandura (1977, 1986). Bandura saw people as "self-organizing, proactive, and self-regulating agents of their psychosocial development" (Bandura et al., 2001, p. 187) whose thinking was the primary influence on their behavior. He made a distinction between outcome expectations and efficacy expectations. Outcome expectancy is a person's estimate that a certain behavior will lead to a certain outcome. Efficacy expectancy is the person's conviction that they can successfully perform the behavior that will produce the outcome (Bandura, 1977). The two expectancies are different because one might have a high degree of certainty in the outcome of a behavior but have a great deal of doubt in one's ability to perform that behavior. A central concept in Social Cognitive Theory is perceived self-efficacy, defined as self-appraisal of one's capability to competently perform a task to produce a certain outcome in a given situation (Bandura, 1989).

Beginning in his own field of psychology, Bandura (1977) based his theory on the assumption that all effective psychological procedures serve to create and strengthen personal efficacy. How strongly a person judges his or her own effectiveness will influence whether a person will even try to cope with a situation, how much effort they expend in coping, and how long they will keep coping in the face of adversities. This affects choice of behavior because people will avoid activities they feel incapable of performing well and choose those where they feel competent. While other factors such as actual capability and incentives also affect behavior choices, self-efficacy is a major determinant.

Bandura felt self-efficacy had little utility as a general construct and was only meaningful when applied to specific areas. Meaningful self-efficacy measurement requires a microanalysis of the task, not a macroanalysis. Bandura (1977) stated that the principles of his theory extended beyond psychological treatment. He and others have since applied them to many other fields. For example, Eccles and her colleagues at the University of Michigan have applied the concept to academic performance, including math performance, and shown it to be a valid predictor of success (Eccles, 2006; Wigfield & Eccles, 2000). Self-efficacy is powerful because it impacts other determinants of behavior.

> [Efficacy] beliefs influence aspirations and strength of commitment to them, the quality of analytic and strategic thinking, level of motivation and perseverance in the face of difficulties and setbacks, resilience to adversity, causal attributions for successes and failures, and vulnerability to stress and depression (Bandura et al., 2001, pp. 187-188).

Thus self-efficacy is related to several other constructs often measured to predict success: commitment, cognitive schemes, motivation, perseverance, resilience, and locus of control. Although a measure of personal efficacy does not directly measure these areas, it provides a central construct to which these other constructs are likely to correspond.

Although self-efficacy is powerful, it does have limitations. The most notable one is that high self-efficacy does not always predict success at a task; a person may perceive himself or herself to be able to master a task yet lack the capability to do so (Bandura, 1977). Optimum self-efficacy is that which is slightly beyond a person's actual capability in order to encourage them to extend themselves and take on a challenging task (Bandura, 1989). Unrealistically high self-efficacy may cause a person to take on a task at which they are doomed to fail. However, such a failure would tend to lower the person's self-efficacy. Because people adjust their self-efficacy through experiences, unduly high self-efficacy is not common. Self-efficacy has been shown to be a good predictor of performance (Bandura, 1989).

Online Learning Theory

Anderson (2008) has offered a theory of online learning based on four attributes of learning proposed by Bransford, Brown, and Cocking in 1999 (cited in Anderson, 2008): learning occurs when an environment is learner centered, knowledge centered, community centered, and assessment centered. Anderson aligns these with the affordances of the worldwide web: the internet is learner centered because it can support individualized and community centered learning activities; it is knowledge centered because it offers access to a vast amount of content and learning activities; it is community centered because it offers multiple formats of synchronous and asynchronous communication; and it is assessment centered because it offers multiple opportunities for assessment by self, peers, and the teacher. Anderson's theory offers a model of multiple interactions between students, content, peers, and teachers using these features of the internet. The importance of Anderson's theory is that is shows online course delivery is a valid format for promoting student learning with a basis in learning theory. Online learning offers unique affordances and is not merely a replication of traditional courses using computers.

Application of the Theories

Math self-efficacy has been shown to be a valid predictor of mathematical performance. Therefore, it ought to be a good predictor of achievement in any of the three developmental math delivery formats. Technology self-efficacy should be a predictor of success in online and hybrid formats that feature extensive use of computers and the internet, but not in the seated format where computers are not used in instruction. Online learning theory supports the idea that online and hybrid formats are based on sound learning theory; this means that some students will be successful in these formats. Measuring technology and math self-efficacies should help identify these students. Those with high technology self-efficacy should have the necessary comfort with computers; students with high math self-efficacy should have the math confidence that will help them succeed in the independent learning environment of online classes.

Implications for the Study

Developmental education is a critical part of the community college's mission to provide open-door access to higher education (Cohen & Brawer, 2003); developmental mathematics is its largest component (National Center for Education Studies, 2003b). There is a rapidly growing demand for online education (Allen & Seaman, 2008; Parsad & Lewis, 2008; Picciano et al., 2010), making it another important component of the community college mission. The flexibility of online and hybrid courses provides access to higher education for students who would otherwise be excluded due to distance from campus or work schedules. Anderson (2008) has shown the internet has affordances which allow online instruction to be based on sound learning theory, yet very few developmental mathematics courses are delivered online (Gerlaugh et al., 2007). The last study that explicitly examined success and academic achievement in online developmental mathematics courses was in 1998 (Ford & Klicka), although more recent studies have examined various aspects of this. Since then, the speed and capabilities of computers, software and the internet have improved exponentially (Engelbrecht & Harding, 2005). Community college developmental educators need more research on factors that lead to success in online education for developmental math students so they can explore effective ways to combine these two important parts of the community college mission.

The literature also clearly indicates that not all developmental students are likely to succeed in an online environment (Boylan, 2002; Ford & Klicka, 1998; Phillip, 2011; Villarreal, 2003; Xu & Jaggars, 2011a, 2011b; Zavarella & Ignash, 2009). Research is needed on factors that will predict success so colleges can help students assess whether or not they are likely to do well in an online course. A multitude of factors have been studied, but social cognitive theory (Bandura, 1986) shows that perceived self-efficacy provides a central construct which is related to many other affective factors. Bandura (2001) also showed self-efficacy must be applied to a specific area to be a useful predictor of performance. For developmental mathematics students in an online environment, the useful predictors are mathematics self-efficacy and technology self-efficacy. While math self-efficacy has been used to study academic achievement in developmental math students and technology self-efficacy has been used to study academic achievement in online students, no study has combined these two predictors. This study addresses that gap in the literature.

CHAPTER 3: METHODOLOGY

The purpose of this study is to examine how well the independent variables of math self-efficacy and technology self-efficacy predict the dependent variable of student achievement in developmental math courses at a community college. These predictors and this outcome were used to identify whether or not there are differences between seated, hybrid, and online sections of the courses.

More than half of new students who arrive at community colleges need to further develop their mathematical skills before enrolling in college-level mathematics courses in order to pursue their educational and career goals (Bailey et al., 2010a)..To meet this need, colleges offer developmental mathematics classes and student support services. Traditional instructional strategies employ a delivery format students have already experienced to repeat mathematical content students have failed to master; these strategies have not been highly successful with developmental students. Colleges are seeking alternative strategies that promote active learning and increase students' chances of success. Computers and the internet have the potential to deliver learning in a way that actively involves students and that offers flexibility to busy adult learners. However, questions have arisen about whether developmental students have the study skills and self-discipline necessary to succeed in an online or hybrid seated/online environment. Because these delivery formats will benefit some students, colleges need a practical way to reliably predict which students are likely to be successful in an environment that relies on computers to deliver some or all of the course content. This study addresses that need by examining two potential predictors of success for developmental mathematics students in online, hybrid and traditional course delivery formats.

A four-part survey was administered to students in the seated, hybrid, and online sections of two levels of developmental math courses at a large suburban community college in North Carolina. Data from the survey were compared to these students' performances on common final exams at the end of the semester. The first portion of the survey gathered demographic data for descriptive purposes, the second part addressed technology self-efficacy, the third part addressed mathematics self-efficacy in the context of a math classroom, and the fourth part addressed math self-efficacy in the context of a math test. Although other measures of performance are possible (e.g., course grade, enrollment in the next math course, persistence), this study uses course-level examination data. The math courses used in this study each have a common final exam given in a proctored, seated environment; this ensures equivalent measures of the dependent variable. Course-level data rather than another long-term measurement are used because not all community college students have the same educational goals. Some seek a degree, but others may take a course to update job skills or for personal enrichment (Hagedorn, 2005).

Research Questions

The following research questions guided the study:

1. To what extent does course-specific mathematics self-efficacy predict performance on a final assessment in a developmental math course?
2. To what extent does technology self-efficacy predict performance on a final assessment in a developmental math course?
3. Do these predictors of success differ among online, hybrid, and traditional face-to-face courses?

Research Design

This study used a quantitative research design employing binomial logistic regression and linear multiple regression. The goal of logistic regression analysis is to correctly predict the category of the outcome variable for individual cases; correct prediction does not imply causality (Tabachnick & Fidell, 2007). Logistic regression determines if the independent variables are significant in predicting the outcome category. In this study, two independent variables (math self-efficacy and technology self-efficacy) were used to predict a single dependent variable (student performance on a common final examination). Assuming logistic regression finds both variables to be significant predictors, the next step was to use multiple regression to build a predictor equation for a particular score on the outcome variable. Multiple regression is commonly used to study the relationship between multiple predictor variables and a single dependent variable. This design helped answer the first two research questions by showing how well the two independent variables predict the outcome dependent variable; repeating the analysis within the various formats while being mindful of their inherent differences was used to answer the third research question.

A previously developed survey and an adapted version of another survey were combined to measure the independent variables; a locally developed 12-question section gathered demographic data including gender, age, race/ethnicity, marital status, family obligations, course enrollment status, and past experience with online and developmental mathematics courses. The Online Technologies Self-Efficacy Survey (OTSES) (Miltiadou & Yu, 2000) was used to measure students' confidence with technologies used in online and hybrid courses. All 28 questions of this instrument were used, although it was slightly modified to update terminology and clarify the wording. Math self-efficacy was measured by an adapted version of the Mathematics Self-Efficacy Scale (MSES) developed by Nielsen and Moore (2003). The original 18-question instrument focused on confidence in math ability at the high school level in the context of the classroom and on a math test. This was adapted into two surveys, 20 questions for MAT 070 and 18 for MAT 080, based on the specific learning outcomes for each of those courses.

For the purpose of this study, an online class is defined as one in which all the instruction takes place using the internet and the Course Compass learning management system. Typically there is little or no personal interaction between the instructor and students except through electronic mail and online discussion boards. The seated sections of the courses are taught in a traditional classroom environment primarily through lecture. Hybrid courses employ the seated format for 50% of course delivery and the online format for the other 50%.

Local approval and written permission to conduct the study (Appendix A) were obtained from the college's Vice-President of Academic Affairs. The Developmental Education department agreed to assist with the study (Appendix B). Data were collected during the fall semester of 2011.

Permission was obtained from the Appalachian State University Institutional Review Board to conduct the study (Appendix C).

Instrument

Two existing instruments, the OTSES and the adapted MSES, were combined with 12 demographic questions for a total of 60 questions (58 for MAT 080). A copy of the composite survey for MAT 070 is included as Appendix D and the two sections of the MAT 080 survey that differed from the MAT 070 survey are included as Appendix E. Permission for use from the author of the OTSES is attached as Appendix F. The MSES is in the public domain.

Online Technologies Self-Efficacy Scale

Miltiadou and Yu created and validated the Online Technologies Self-Efficacy Scale (OTSES) at Arizona State University in 2000. Their purpose was to measure student confidence in the technologies used in online courses, such as web browsers, discussion boards and electronic mail. These authors felt technology self-efficacy is especially important to online students because those who are uncomfortable with online technologies are distracted from course content, instead spending much of their time learning to use the technology. Bandura (1986) defined self-efficacy beliefs as individuals' "judgments of their capability to organize and execute courses of action required to attain designated types of performances" (p. 86). Miltiadou and Yu (2000) noted that while there were many instruments designed to measure self-efficacy, none focus on student perceptions of confidence with technology; they created the OTSES to fulfill this need.

Miltiadou and Yu conducted a research study of 330 students at five educational institutions. Based on the results they made revisions and produced the final version of the instrument. Construct validity and internal consistency were assessed to validate the instrument. A factor analysis was performed which showed the original four scales could be collapsed into a single scale. The internal consistency reliability estimate for the final instrument was calculated to be .95 from the Cronbach's coefficient alpha. The survey contains 28 questions using a four-point Likert scale of "Very Confident," "Somewhat Confident," "Not Very Confident," and "Not Confident at All."

Mathematics Self-Efficacy Scale

Nielsen and Moore created and validated the Mathematics Self-Efficacy Scale (MSES) in 2003 based on Bandura's (1986) assertion that task self-efficacy must be content and context specific. They identified nine major concepts from high school algebra and geometry; from these concepts, they created nine questions and asked students to rate their confidence to successfully solve associated problems in two contexts: in a math classroom and on a math test. Nine questions address each of these subscales for a total of 18. Responses are on a five-point Likert scale ranging from "Not at all Confident" to "Very Confident."

The instrument was administered to 302 high school students in schools across Melbourne, Australia and surrounding districts. Students also completed the mathematics subscale of Marsh's Self-Description Questionnaire III (SDQIII), designed to assess mathematics self-concept, and provided demographic information. Results showed that scores on the class and test context self-efficacy subscales were highly correlated ($r = .74$) and together explained 49% of the total score variance. Both classroom and test environment scores demonstrated internal reliability (Cronbach's alphas = .86 and .90); the combined items also showed strong internal consistency, Cronbach's alpha = .93. Convergent construct validity was shown by significant correlations between MSES results and past math grades, desired math grade, and the results of the SDQIII (Math). Discriminant validity was shown by lack of correlation of MSES score with desired English grade.

As previously noted, the MSES has been adapted into two surveys for this study, a 20-question one for MAT 070 and an 18-question one for MAT 080, based on the learning outcomes for each of those courses. This is in keeping with the need to be content specific when measuring self-efficacy (Bandura, 1986; Nielsen & Moore, 2003). The developmental math department at the college under study has verified that the questions reflect learning outcomes for each course. This expert review serves to help validate the modified instrument, along with internal reliability calculations based on the survey responses.

Rationale for the Design

Mathematics self-efficacy and technology self-efficacy are the independent variables in this study. These variables were chosen based on an extensive review of the literature on factors affecting achievement for community college developmental mathematics students. The conceptual framework identified for the study and the focus on developmental mathematics students in settings with various amounts of computer use suggested mathematics self-efficacy and technology self-efficacy as the most appropriate independent variables.

The two independent variables deal with self-efficacy, a person's confidence in her or his ability to successfully perform a specific task. Self-efficacy has been shown to be a good predictor of performance and to be highly related to other predictors of performance such as commitment, motivation, perseverance, resilience, locus of control, subject anxiety, and subject self-concept (Bandura et al., 2001). To be a valid predictor of performance, self-efficacy must be measured as applied to a specific task (Bandura, 1986). For developmental mathematics students, the relevant task is mathematics; therefore mathematics self-efficacy is a potentially good predictor of mathematics performance. The other dimension of the study is the various course delivery formats: traditional seated, hybrid, and online. Because hybrid and online components require extensive work with computers and the internet, these students need to be proficient at using technology. Therefore, technology self-efficacy was the final independent variable in the study.

The single dependent variable in the study was student performance; this variable was measured by student's scores on common final examinations. The final examinations were created by the developmental mathematics department. They are a cumulative test of all the content in the courses. Each is administered by pencil and paper in a seated, proctored environment for students in all sections. The standard content and delivery mode make this an ideal course-level outcome instrument.

Role of the Researcher and Ethical Considerations

The researcher is an Associate Dean and instructor in a different department at the college where the study was done. Because of the college's mandatory prerequisite structure, none of the students who were surveyed could possibly have had the researcher as an instructor during the study. Some students in the study could have been in the division where the researcher is Associate Dean, but very few would have had contact with him. The Associate Dean position at the college is filled by full-time instructors who are given release time for administrative duties that assist the division Dean. Associate Deans have no authority to make academic or disciplinary decisions regarding students. However, the researcher was aware of the implied authority of his position at the college and was diligent to maintain a separate role as a researcher during the study, focusing on the collection and analysis of data.

The link to the survey instrument was provided to developmental mathematics faculty to share with their students at the beginning of the fall 2011 semester. Instructors also received a letter explaining the survey and its purpose. The survey itself was on deployed on SurveyMonkey, a commercial survey website; this allowed the results to come directly to researcher and reduced the burden on developmental math instructors. Faculty members were requested to explain the survey and the research goals of the project to students and to solicit participation. Students were asked to complete the survey by following the link provided by their instructor and posted in each classroom. Participation by faculty in posting the survey and by students in completing it was voluntary. A random drawing was held which awarded a prize to one respondent to increase participation. The researcher did not have any direct contact with the students during the study.

Data Collection Procedures

The survey was administered during the first two weeks of the fall semester of 2011 to students enrolled in MAT 070, Introductory Algebra, and MAT 080, Intermediate Algebra. These courses are the final two in a sequence of three developmental mathematics courses. Topics in MAT 070 include signed numbers, exponents, order of operations, simplifying expressions, solving linear equations and inequalities, graphing, formulas, polynomials, factoring, and elements of geometry. Topics in MAT 080 include factoring, rational expressions, rational exponents, rational equations, radical equations, quadratic equations, systems of equations, inequalities, graphing, functions, variations, complex numbers, and elements of geometry. Both are offered in seated, hybrid, and online formats. Table 1 shows the course formats offered and potential (not actual) enrollment for fall 2011.

Table 1. Sections Offered and Potential Enrollment for Fall 2011

Course	Traditional Sections (Enrollment)	Hybrid Sections (Enrollment)	Online Sections (Enrollment)	Total Sections (Enrollment)
MAT 070	15(375)	7(175)	3(75)	25(625)
MAT 080	10(250)	4(100)	2(50)	16(400)
Total	25(575)	11(275)	5(125)	41(1025)

MAT 070, Introductory Algebra, and MAT 080, Intermediate Algebra, are four semester hour course with three hours of lecture and two hours of laboratory. Traditional seated sections of the courses meet in a classroom where new concepts are introduced via lecture and students are given opportunities for guided practice, either individually or in small groups. Laboratory activities are incorporated into class meeting hours, so there is no separate lab session. Online sections are delivered via the Prentice-Hall Course Compass learning management system and use MyMathLab software. Students purchase access to the course website and an electronic version of the textbook as a package. The software uses interactive multimedia to present the course concepts with practice activities embedded in the presentation. Assignments and quizzes are done online. Students meet at the beginning of the semester for a mandatory orientation session and again at the end of the semester for a proctored written final examination. Hybrid courses use the same software, but it is used for assignments and quizzes only. Concepts are introduced through lecture during class meetings. Lecture is used for 50% of the course time while the remaining 50% is used for independent computer work. Both courses use the same text books for all sections; online courses use an electronic version while hybrid and seated classes use a printed version, the electronic version, or both. Students in MAT 080 must pass the final examination to pass the course but this is not required in MAT 070.

The survey was made available online at the beginning of the semester to each student enrolled in any section of the two courses. The survey was available for two weeks. Students were encouraged to participate but allowed to decline. Anonymity was assured by having students provide their student identification number but not their name. To encourage responses to the survey, a drawing was held to award a prize to one randomly selected respondent. Students were asked in the survey if they agreed to have their contact information looked up from their student identification number if (and only if) they won the drawing; they also had the option to decline to participate in the drawing. Scores on the final examination were obtained at the end of the semester from college records, again identified only by student identification number. The results of the surveys and the outcome data were analyzed to determine which combination of independent variables best predicted student performance. Descriptive, correlation, logistic regression, and multiple regression analyses were used.

Participant Selection

The college chosen as the site of this study is a large suburban public community college that serves two counties in North Carolina. The college offers three levels of developmental mathematics courses, MAT 060, MAT 070, and MAT 080. Courses are offered in traditional seated, hybrid, and online formats (except MAT 060, which is not offered online). MAT 070, Introductory Algebra, and MAT 080, Intermediate Algebra, were chosen for this study. Both are offered in all three formats and have a proctored pencil and paper cumulative final examination. All MAT 070 and MAT 080 students at the college in fall 2011were invited to participate in the study.

Convenience sampling was used in this study. However, because the college offers developmental mathematics classes in all three delivery formats, and because the developmental mathematics program there employs multiple research-based best practices (Boylan, 2002), this college was an excellent candidate for this study. At the college, the developmental mathematics students are stratified into three levels; this study sought participation from the entire second and third levels, MAT 070 and MAT 080 students. This assured the largest possible number of participants. MAT 060, the other level of developmental math, was not included in the study because it is not offered in all three formats.

The college has a quality developmental mathematics program. Among the critical success factors measured by the North Carolina Community College System (NCCCS), two deal with developmental math. The standard states that 75% of developmental math students must receive a grade of C or better in developmental math classes and 80% must receive a grade of D or better in their first college-level math class. The college has consistently exceeded these standards. In the 2009-2010 academic year, 81% of students received a C or better in their developmental math class and 91% received a D or better in their first college-level math class. This continues a trend of excellence; in 2008-2009 the numbers were 81% and 89% respectively, and in 2007-2008 they were 82% and 89% (NCCCS, 2010).

Data Analysis

A correlational research design was used to analyze the survey items. Binomial logistic regression was used first to determine if the independent variables were significant in predicting if students fall in the category of success (at or above the mean score on the dependent variable) or non-success (below the mean score on the dependent variable). To account for differences in the final examination scores between the two classes, scores were converted into standard scores. For logistic regression it was necessary to dichotomize the continuous variable of standard scores into a categorical value. In order to assure equal probabilities of success/non-success outcomes, scores at or above the mean were considered successful.

The independent variables (average math self-efficacy score and average technology self-efficacy score) that proved to be significant were then used to create a predictor equation for the continuous final score dependent variable using multiple regression. Multiple regression is appropriate for this study because it can show the relationship between multiple independent variables and a single dependent variable (Fraenkel & Wallen, 2003). When two variables are found to be correlated, it means scores within a certain range on the first variable are associated with scores within a certain range on the second variable. Correlation can be either positive or negative. Positive correlation means high scores on one variable are associated with high scores on the other variable, or low scores on one variable are associated with low scores on the other variable. Negative correlation is the opposite; high scores on the first variable are associated with low scores on the second, and vice versa. When variables are correlated, it becomes possible to predict a score on one variable by measuring the value of the other. The measured variable is known as the predictor variable and the other (predicted) variable is known as the criterion or outcome variable. In the case that only one of the predictor variables is significant, multiple regression becomes simple linear regression and provides the same information.

In the study, scores for Technology Self-efficacy (TSE) and Mathematics Self-efficacy (MSE) were obtained by averaging the individual responses. Independent variables that proved to be significant based on the logistic regression analysis were used in the multiple regression analysis to predict the outcome variable of mathematics performance based on final examination score. Because two different sets of survey questions were used to measure math self-efficacy for the two courses, data between the two groups were tested to see if they differed on math self-efficacy scores and if the trends differed. When necessary, standard scores were computed to remove the differences. Multiple regression was used to determine if a combination of the predictor variables best explains variations in the outcome variable. Demographic factors were not used as predictors in this study but were used to examine characteristics of the groups.

Trustworthiness and Validity

The trustworthiness of the proposed study is affected by several factors. External validity deals with how results of the study could be generalized. External validity is imperfect in this study since data were obtained from students in only one college. Internal validity, the approximate truth of inferences in cause-effect relationships (Trochim & Donnelly, 2008), is limited because only one pair of developmental math courses were studied, and only during one semester. A large number of factors may relate to student success in developmental mathematics in the various formats; this study only uses a few, although variables were logically chosen to be as comprehensive as possible. Because participation was voluntary, the number of student responses was not certain. The data set was imbalanced due to unequal course offerings among the three formats (25 traditional seated, 11 hybrid, and five online sections were offered in fall 2011). Implications of this imbalance were considered during the data analysis. Students self-reported information on the surveys, which cannot be guaranteed to be accurate. The data analysis must assume accurate reporting by the students. Because all sections of MAT 070 and MAT 080 have the same content and learning outcomes regardless of mode of delivery, the data analysis must assume all students in the various modes of delivery were exposed to the same content and that similar teaching methods were employed within each format. Another limitation is that the math self-efficacy portion of the instrument was modified from the original validated version. This was compensated for by having the developmental math department provide an expert review of the modified questions and by calculating internal reliability based on the responses in this study.

CHAPTER 4: RESULTS

The purpose of this study was to examine if the independent variables of math self-efficacy and technology self-efficacy predict the dependent variable of student achievement in developmental math courses at a community college. The following research questions guided the study:

1. To what extent does course-specific mathematics self-efficacy predict performance on a final assessment in a developmental math course?
2. To what extent does technology self-efficacy predict performance on a final assessment in a developmental math course?
3. Do these predictors of success differ among online, hybrid, and traditional face-to-face courses?

In this chapter the descriptive statistics and findings of the analysis are presented based on the collected data. The statistical analysis was conducted using the Statistical Package for the Social Sciences (SPSS) Version 19.

Descriptive Statistics

A survey was administered in the fall semester of 2011 to students enrolled in MAT 070, Introductory Algebra, and MAT 080, Intermediate Algebra. Both are offered in seated, hybrid, and online formats. The total number of potential study participants in fall 2011 was 1025. After registration ended and enrollment was confirmed, 887 students were enrolled in the courses.

The survey was published online and made available to all enrolled students. For each response, the student ID number was used to confirm the respondent was currently enrolled in one of the two courses. Students were encouraged to participate but it was made clear that participation was voluntary. A random drawing for a prize for one participant (who agreed to be considered for the prize) was used to promote participation. One hundred and forty-nine students completed the survey, for a participation rate of 16.8%. Of the 149 responses, 104 (69.8%) were from MAT 070 and 45

Table 2. Demographics of the Sample as a Percentage of the Sample

Demographic	Hybrid (n = 44)	Online (n = 17)	Traditional (n = 69)	Sample (N = 130)
Gender				
Female	77.3	82.4	60.9	69.2
Male	22.7	17.6	39.1	30.8
Race/Ethnicity				
American Indian			1.4	.8
Asian			1.4	.8
Black	4.5	29.4	18.8	15.4
Hispanic	6.8		4.3	4.6
White	81.8	70.6	69.6	73.8
Other	6.8		4.3	4.6
Age category				
25 or younger	70.5	35.3	58.0	59.2
Over 25	29.5	64.7	42.0	40.8
Married?				
No	75.0	52.9	76.8	73.1
Yes	25.0	47.1	23.2	26.9
Hours worked per week				
0	45.5	47.1	34.8	40.0
1 – 10	13.6	5.9	5.8	8.5
11 – 20	13.6	23.5	14.5	15.4
21 – 30	6.8		15.9	10.8
31 – 39	11.4		13.0	10.8
40 or more	9.1	23.5	15.9	14.6
Dependents?				
No	63.6	29.4	63.8	59.2
Yes	36.4	70.6	36.2	40.8
Hours enrolled				
4 – 11	15.9	23.5	30.4	24.6
12 or more	84.1	76.5	69.6	75.4
Last college course				
First semester in college	38.6	5.9	26.1	27.7
Last semester	45.5	70.6	49.3	50.8
Within 1 year	9.1	17.6	1.9	13.8
1 – 5 years			5.8	3.1
6 or more years	6.8	5.9	2.9	4.6
Online course before?				
Yes	50.0	94.1	47.8	54.6
No	50.0	5.9	52.2	45.4
Developmental math before?				
Yes	31.8	47.1	58.0	47.7
No	68.2	52.9	42.0	52.3

(30.2%) were from MAT 080. By course type, 51 (34.2%) students were from hybrid courses, 20 (13.4%) were from online courses, and 78 (52.3%) were from traditional courses. By the end of the semester 19 of the students who responded had withdrawn from their course and had to be removed from the study because no outcome data were available for them. The final population size (*N*) for the sample was 130. Of these remaining 130 cases, 38 (29.2%) were from MAT 080 and 92 (70.8%) were from MAT 070. Hybrid courses accounted for 44 (33.8%) of the cases, online courses accounted for 17 (13.1%), and traditional courses for 69 (53.1%). Table 2 reports the demographics of the sample.

Common written final examinations are given to all students in MAT 070 and MAT 080 at the end of each semester; these exams were used to measure student success in this study. The statistics for the instruments based on the sample used in this study for the fall semester of 2011 are presented in Table 3.

Table 3. Statistics of Common Final Assessments

	Hybrid		Online		Traditional		Total	
Course	*n*	M (SD)	*n*	M (SD)	*n*	M (SD)	*N*	M (SD)
MAT 070	39	81.44 (14.01)	11	84.36 (16.61)	42	74.60 (13.28)	92	78.66 (14.37)
MAT 080	5	89.80 (8.84)	6	96.00 (6.07)	27	77.11 (13.32)	38	81.76 (13.98)

Reliability of the Final Examination Evaluation Instrument

The college uses a comprehensive final examination instrument as part of the evaluation of overall student success in meeting the learning objectives for the courses in this study. The final examinations in MAT 070, Introductory Algebra, and MAT 080, Intermediate Algebra, are 50-question tests that were developed by the developmental math instructors at the college. These instructors have many years of experience working and teaching in the field of developmental mathematics, and each has taught both of the courses in this study multiple times. Answer formats on the exams are multiple-choice, numerical, and graphing.

The internal consistency of the final examination instruments was analyzed using Cronbach's alpha, which is commonly used to prove the reliability of such instruments. Cronbach's alpha produces pairwise correlations between items on an instrument to measure internal consistency, producing a number between zero and one (Fraenkel & Wallen, 2003). A result of 0.6 – 0.7 is generally considered acceptable, while a result above 0.8 is considered good. Cronbach's alphas for the instruments in this study were .85 for the MAT 070 final examination and .88 for MAT 080. Detailed data from 102 MAT 070 examinations and 80 MAT 080 examinations completed in fall 2011, the term used in this study, were used to compute these coefficients.

Reliability of the Survey Instruments

All 149 survey responses were used to analyze the internal reliability of the survey instruments. Because the MAT 070 and MAT 080 surveys had different questions in the mathematics self-efficacy (MSE) sections, three different analyses were performed. The 28 common technology self-efficacy (TSE) questions taken from the Online Technology Self-Efficacy Survey (OTSES) (Miltiadou & Yu, 2000) were the same on both surveys and were analyzed for the entire group; then the MSE questions adapted from the Mathematics Self-Efficacy Scale (MSES) (Nielsen & Moore, 2003) for MAT 070 (20 questions) and MAT 080 (18 questions) were analyzed separately.

According to Miltiadou and Yu (2000), the OTSES scale has good internal consistency, with a Cronbach's alpha coefficient reported of .95. In the current study, Cronbach's alpha was .96. Nielsen and Moore (2003) report good internal consistency for the MSES, with a Cronbach's alpha of .93. In the present study, Cronbach's alpha was .96 for the MAT 070 MSE questions and .98 for the MAT 080 MSE questions. Descriptive statistics for the independent variables are presented in Tables 4 and 5. Item scores for TSE range from 1 to 4 while item scores for MSE range from 1 to 5.

Table 4. Descriptive Statistics of Average TSE Scores by Delivery Mode

Hybrid		Online		Traditional		Total	
n	M (SD)	*n*	M (SD)	*n*	M (SD)	*N*	M (SD)
44	3.55 (.56)	17	3.80 (.28)	69	3.68 (.43)	130	3.65 (.43)

Table 5. Descriptive Statistics of Average MSE Scores by Course and Delivery Mode

	Hybrid		Online		Traditional		Total	
Course	*n*	M (SD)	*n*	M (SD)	*n*	M (SD)	*N*	M (SD)
MAT 070	39	3.89 (.72)	11	4.06 (.43)	42	3.88 (.85)	92	3.91 (.76)
MAT 080	5	4.49 (.36)	6	4.64 (.37)	27	3.85 (.92)	38	4.06 (.86)

Data Analysis

The OTSES uses a 4-point Likert scale ranging from "1 – Very Confident" to "4 – Not Confident at All." The MSES uses a 5-point Likert scale with the same descriptors on the end points. To clarify data interpretation, item scores from these scales were reversed so that a higher score corresponds to higher self-efficacy. This reversal is reflected in Tables 4 and 5 above. An average technology self-efficacy (TSE) variable was computed by summing the response scores for each case and dividing by 28, the number of questions. An average mathematics self-efficacy (MSE) score was produced in the same manner, taking into account the different number of MSE questions in the MAT 070 and MAT 080 instruments. These variables serve as the independent variables in the analyses.

To account for differences in the two final examination instruments used in MAT 070 and MAT 080, raw exam scores were converted into standard scores by subtracting the appropriate mean and dividing by the appropriate standard deviation. These results were combined in a standard score variable which represents level of success as measured by academic achievement for students. Because the means and standard deviations for average MSE scores for the sample were virtually identical for MAT 070 and MAT 080 (see Table 4), nothing was to be gained by converting to standard scores. The TSE instrument was the same for both courses.

Each of the variables was examined for normality. The distributions of the average MSE and the standard exam score variables were reasonably normal, but the average TSE variable had a very high negative skew. It had a J-shaped distribution with 36 values of 4, indicating a response of "Very Confident" on all 28 survey items. Figure 1 shows the distribution of scores.

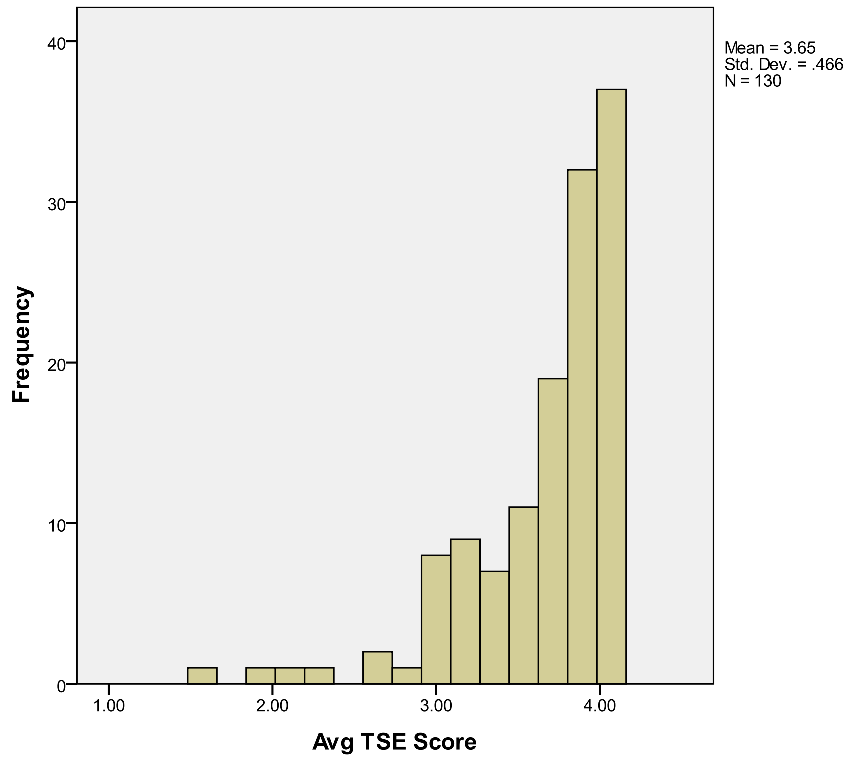

Figure 1. Distribution of average technology self-efficacy scores. The vertical axis shows the frequency of scores and the horizontal axis shows the average technology self-efficacy scores. A score of 1 indicates an average response of "Not Confident at All" while a score of 4 indicates an average response of "Very Confident."

Binomial logistic regression was used to determine which, if any, of the independent variables was a good predictor of the dependent variable. Logistic regression does not require that the independent variables be normally distributed, but it does require that they are not highly correlated to avoid problems with multicollinearity (Tabachnick & Fidell, 2007). To check this, the relationship between average MSE and average TSE was investigated using a Pearson product-moment correlation coefficient. There was a small correlation between the variables, $r = .29$, $N = 130$, $p = .009$. Logistic regression also requires a categorical dependent variable. This was obtained by dichotomizing the standard exam score variable about the mean to ensure equal distributions of success and non-success scores. Scores at or above the mean were coded as 1, representing a high level of success in the course, and scores below the mean were coded as 0, corresponding to a low level of success.

Direct logistic regression using the Enter method was performed to assess the impact of average TSE score and average MSE score on the likelihood that respondents would have a high level of success on their final examination. The full model containing both predictors was statistically significant, χ^2 (2, N = 130) = 6.54, p = .038, indicating the model was able to distinguish between respondents with high and low success scores. The model as a whole explained between 4.9% (Cox and Snell R squared) and 6.6% (Nagelkerke R squared) of the variance in success scores, and correctly classified 59.2% of cases. As shown in Table 5, only one of the independent variables made a unique statistically significant contribution to the model (average MSE score). Average MSE score recorded an odds ratio of 1.87, indicating students with higher MSE were almost twice as likely to achieve success as those who had lower MSE, controlling for the other factor in the model.

Table 6. Logistic Regression Predicting the Likelihood of Success on the Final Examination

	B	S.E.	Wald	*df*	*p*	Odds Ratio	95% CI for Odds Ratio	
							Lower	Upper
Average TSE Score	-.39	.42	.90	1	.34	.67	.30	1.52
Average MSE Score	.63	.26	5.95	1	.02*	1.87	1.13	3.09
Constant	-.76	1.52	.26	1	.61			

Note. CI = confidence interval
* $p < .05$

With average MSE established as a predictor of success, the next step was to use linear regression to create a predictor equation. A Pearson product-moment analysis showed a small, positive correlation between average MSE and standard score, $r = .267$, $N = 130$, $p = .001$, with higher levels of MSE associated with higher scores. The regression model explained 7.1% of the variance in standard score and was significant, F (1,130) = 9.827, p = .002. Based on the unstandardized coefficients returned by the model, the predictor equation is:

$$.338 * \text{average MSE} - 1.335 = \text{standard score.}$$

This equation could be converted to predict raw score by multiplying both sides by the standard deviation and then adding the mean to both sides.

To examine how well MSE predicted standard score in the various delivery modes, the analysis was repeated for hybrid, online and traditional courses separately. Standard scores for the final examination were recomputed using the appropriate means and standard deviations for each mode. To account for possible differences introduced by the different instruments used to measure MSE in the two courses, average MSE scores were converted to standard scores for each delivery mode. Because average MSE had been shown to be a significant predictor for the group, it was not necessary to repeat the logistic regression analysis. A regression analysis was performed for each delivery mode.

A Pearson product-moment analysis showed a moderate, positive correlation between average standard MSE and standard score for hybrid courses, $r = .358$, $n = 44$, $p = .009$, with higher levels of MSE associated with higher scores. The regression model explained 12.8% of the variance in standard score and was significant, $F\ (1, 44) = 6.155$, $p = .017$. Based on the unstandardized coefficients returned by the model, the predictor equation is:

$$.357 * \text{average standard MSE} = \text{standard score.}$$

The constant was zero. The models for online and traditional courses did not reach significance.

In summary, a binomial logistic regression analysis showed that MSE was a valid predictor of success for the developmental math students in this study but TSE was not. Linear regression analysis produced a valid equation to predict standard score from average MSE score. When separated into groups according to course format, MSE was only a valid predictor for students in hybrid courses. Chapter 5 will provide an analysis of these results and what answers they provide to the research questions. It will also discuss the implications of the results, along with the assumptions and limitations of the study. Finally, it will make recommendations for further research.

CHAPTER 5: FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

This chapter summarizes the findings of the study, presents conclusions based on analysis of the findings, and makes recommendations for further research. The implications the data have for each of the research questions are considered and applications of the findings for students, faculty, and administrators are discussed. Also, limitations of the findings are discussed and recommendations are made for further research.

Summary of Findings

The purpose of this study was to test theories that relate mathematics self-efficacy and technology self-efficacy to student achievement for developmental math students at a large suburban community college. The independent variable of mathematics self-efficacy was defined as a student's belief in his or her own ability to successfully perform mathematical tasks (Hackett & Betz, 1989). The independent variable of technology self-efficacy was defined as a student's belief in his or her ability to use computers and to learn new computer skills (Lim, 2001). The dependent variable of student achievement as a measure of success was defined as the results on a common comprehensive final exam in two levels of developmental mathematics classes. Demographics were also measured for descriptive purposes.

Analysis of demographic factors (see Table 2 on page 50) shows the majority of students who participated were female (69.2%), White (73.8%), 25 years old or younger (59.2%), single (73.1%), worked 11 or more hours per week (51.5%), did not have dependents (59.2%), were enrolled full time (75.4%), took their last college course during the previous semester (50.8%), had taken an online course before (54.6%), and had not taken a developmental math class before (52.3%). Considered by delivery mode, hybrid students had generally the same profile as the total sample. Traditional students also had the same general profile, with the exception that the majority of them (58.0%) had taken a developmental math course before.

There were several items of note about the online students, although there were only 17 in that category. These students had the highest representation of females (82.4%) and Blacks (29.4%). Unlike the other modes, students over 25 years old represented the majority (64.7%) of these students. The online group had the highest percentage of students who worked full time (23.5%) but also had the highest percentage of students who did not work at all (47.1%). While the majority of students in the other modes did not have dependents, 70.6% of online students did have them. Most of the online students (94.1%) had taken an online course before.

The survey instrument used to measure the independent variables in the study had three components: a 12-question section on demographics, a 28-question section on technology self-efficacy (TSE), and a 20-question (MAT 070) or 18-question (MAT 080) section on mathematics self-efficacy (MSE). Logistic regression was used to determine if the independent variables of TSE and MSE could reliably predict success as measured by academic achievement on the final exam, which served as the dependent variable. Significant predictors were then analyzed using linear regression to produce a predictor equation.

The following sections will present how the research findings bear upon the three research questions, which are listed below.

1. To what extent does course-specific mathematics self-efficacy predict performance on a final assessment in a developmental math course?
2. To what extent does technology self-efficacy predict performance on a final assessment in a developmental math course?
3. Do these predictors of success differ among online, hybrid, and traditional face-to-face courses?

Question One: Mathematics Self-Efficacy

Logistic regression analysis showed that MSE was a significant predictor of success on the final examination. This confirms the finding by Spence and Usher (2007) that math self-efficacy is an important predictor of mathematics achievement for community college students and extends it specifically to developmental math students. While significant, the logistic regression model explained only between 4.9% and 6.6% of the variance in standard scores. This indicates that while MSE is a valid predictor of student success, it alone is not a very strong one. On the other hand, the odds ratio of 1.87 indicates that students with higher MSE were almost twice as likely to achieve higher scores as those with lower MSE.

The MSE survey section had two subsections, MSE-Classroom and MSE-Test. The question might be asked if the model would be improved by using these subscales as separate predictors. However, a Pearson product-moment analysis showed these subscales were highly correlated, $r = .71$, $N = 130$, $p < .0005$; therefore, they could not be used as separate predictors without raising multicollinearity concerns. Nielsen and Moore (2003) found a similar correlation between their classroom and test subscales, $r = .74$.

The regression analysis showed a small, positive correlation between average MSE and standard score, $r = .267$, $N = 130$, $p = .001$, with higher levels of MSE associated with higher scores (as theory would predict). The regression model explained 7.1% of the variance in standard score and was significant, $F\,(1,130) = 9.827$, $p = .002$. This confirms the finding that MSE alone is a valid but not very strong predictor of success as measured by academic achievement. The predictor equation from the regression model is:

$$.338 * \text{average MSE} - 1.335 = \text{standard score.}$$

This can be converted to predict raw score by multiplying both sides by the standard deviation and adding the mean to both sides. For MAT 070, the resulting equation is:

$$4.86 * \text{average MSE} + 77.33 = \text{raw score.}$$

For MAT 080, the equation is:

$$4.73 * \text{average MSE} + 80.43 = \text{raw score.}$$

The fact that this study shows that MSE predicts success could imply that mathematics self-efficacy causes academic achievement, but that is not a correct assumption. Bandura (1989) observed that while self-efficacy is a factor in successful performance, successful performance also positively affects self-efficacy. When applied to mathematics, this means the interplay is between mathematical confidence and mathematical achievement. Ma and Xu (2004) studied the causal ordering relationship between attitude toward mathematics and achievement in mathematics; they found that achievement has causal predominance over attitude. In terms of the present study, this would mean that mathematics success is a greater cause of math self-efficacy than vice versa.

In summary, the answer to the first research question, based on the data in this study, is that confidence in mathematic ability as measured by average MSE upon class entry predicts performance on a final assessment in a developmental math class to a significant but not very strong extent. It is a valid predictor of success as measured by academic achievement and would offer useful insight about potential success to a student or an educator advising a student, but would be strengthened by use in conjunction with other valid predictors of success. Other possible predictors include the cognitive and affective factors discussed in Chapter 2; further research is needed to determine which factors might best supplement MSE.

Question Two: Technology Self-efficacy

The logistic regression analysis showed average technology self-efficacy (TSE) score was not a significant predictor of success on the final examination. This finding agrees with the results of a similar study of TSE by DeTure (2004) but not with the results for students at the same college used in this study by Jones (2010). The primary reason TSE did not prove to be a significant predictor in the present study is simply because almost all students reported very high TSE. Of the 130 participants, 36 reported perfect average TSE scores of 4.0, and the mean was 3.65. Obviously if almost all the scores are high, the variable will not be a good predictor of anything. There are several possible reasons the scores were so high.

Practical necessities in taking the data may have elevated scores. Ideally, the data should have been measured as part of the screening and advising process for students, just after placement testing. This was not practical in this study so data were taken very early in the semester, within the first two weeks, to be as predictive as possible. However, this means that students in hybrid and online sections would have already been routinely practicing many of the scale items measured by the survey. This would raise their self-efficacy in those areas and lead to higher scores than may have been recorded before the semester.

Another practical necessity in gathering data that may have affected TSE scores is the way the survey was deployed. To reduce the burden on the developmental mathematics instructors, the survey was placed on a commercial website and the link was provided to students. This allowed data to come directly to the researcher. However, an unintended side-effect was that only students comfortable with using a link to access a website were able to take the survey. It is possible some students did not take the survey because they lacked confidence in the very skills the survey was measuring. In retrospect, also providing a paper and pencil form of the survey as an alternative may have improved the distribution of TSE scores.

A broader reason the scores were so high has to do with the way the internet has permeated U.S. society. When Miltiadou and Yu created the OTSES in 2000, internet skills may have been less common than they are today. The students taking the survey, who were mostly younger than 25 years of age, have grown up in a society that takes technology literacy for granted. It is no wonder that the majority of students expressed high confidence in their ability to perform the basic internet tasks covered by the survey such as using a browser, using email, and using a discussion board.

However, the fact that most students are fluent with technology and have high technology self-efficacy does not mean that all are comfortable with technology. Some older students and students from lower socioeconomic classes, for example, may not have had the opportunity to become confident in using technology. It is noteworthy that in this particular study, however, students over 25 years of age and students 25 years of age and younger had the same mean average TSE scores (3.65). Rather than using TSE as a predictor of success, a better procedure might be the use of a computer skills placement test. Students lacking the necessary skills would not be allowed to take online or hybrid classes until they had passed an introductory computer class.

The answer to the second research question then, is that the data in this study show that technology self-efficacy was not a significant predictor of performance on a common final assessment. Most students reported very high TSE regardless of their performance on the assessment. The implication is that a computer placement test would probably serve students better than a predictive survey on TSE. However, TSE might be a better predictor if the data were gathered differently.

Question Three: Differences by Delivery Method

The regression analysis produced a significant model for hybrid courses, but not for the other two delivery methods. An examination of the scatter plots for average standard MSE versus average standard score of the data for each delivery mode showed that hybrid students were more realistic in estimating their confidence in mathematical ability as reflected by scores on the final examination. Traditional students tended to report more confidence than their performance demonstrated while online students tended to report less. The small number of online students, $n = 17$, also may have affected the ability of that model to reach statistical significance.

Another reason students in hybrid courses obtained the same results as the entire group was that the demographic analysis showed they are most representative of the composite group. Students in hybrid courses, with both seated and online components, seem to constitute the heart of the group, with online and traditional students at the extremes. The valid model obtained for hybrid students seems to support the previous finding that average MSE is valid predictor for developmental mathematics students in general rather than suggest that it is only a valid predictor for hybrid students among the three delivery modes. The answer to the third research question, then, is that average MSE alone is a valid predictor within each delivery mode only insofar as students in that mode are representative of developmental math students in general. The data in this study only show MSE to be a direct predictor of success for students in hybrid courses.

It is important to remember that the purpose of this study is to predict success as measured by academic achievement for students who have tested into developmental mathematics but not yet enrolled in a course. At that time, all such students are developmental students in general, represented by data for the entire group. This study shows MSE is a valid predictor of success under those circumstances. The data set used for analysis by group, however, represents students who had already selected a certain delivery mode. If these students had taken an MSE survey prior to enrolling, they may have chosen a different delivery mode based on their score. Therefore, the fact that MSE is a valid predictor of success for the overall group of developmental math students is more important than the fact that it was a valid predictor for only one of the existing groups.

Implications for Practice and Policy

The results of this study have implication for both practice and policy within community colleges. There are implications for students, faculty, and administrators. Decisions based on these findings could have a direct impact on the success of developmental mathematics students.

Implications for Students

An important finding of this study is that technology self-efficacy was not a significant predictor of success for the entire group or for students taking the course in the various delivery modes. This indicates that confidence in technology ability alone is not enough to ensure success in a course that includes a large online component. While the lack of such confidence presents an obstacle to students in hybrid and online courses, this study makes it clear that students should not rely on TSE alone in deciding to take a course in those formats.

On the other hand, the study found that mathematics self-efficacy is a predictor of success for developmental mathematics students in general. Students who are informed about their level of MSE through instruments such as the ones used in this study will have valuable information about their potential for success in the course. Although this information does not explicitly predict success in a particular delivery mode, it could be useful as students decide which delivery mode is best suited for them. Because hybrid and online courses are structured differently than traditional classes and require more independent work, students with low MSE may wish to avoid them while students with high MSE may feel equipped to face the additional challenge those courses pose.

Implications for Faculty

Community college faculty members are faced with the challenge of accurately advising a large number of students with whom they are not personally familiar. This is particularly true of developmental education faculty since students typically take developmental courses at the beginning of their academic careers as prerequisites to college-level courses. The more information advisors have about students, the better advice they will be able to give. By having students complete an MSE survey, advisors will gain valuable insight about their potential for academic achievement. They may wish to advise student with low MSE to take traditional face-to-face classes which offer them more contact with faculty and other students while they build confidence in their mathematical abilities. For students with high MSE scores, faculty advisors can arm them with encouragement about their potential for success and explore with them whether they feel an online or hybrid class would suit their individual learning preferences.

Although TSE was not a significant predictor of success in this study, the findings offer an important reminder to faculty. Because most students, like the ones in this study, are highly confident in their technology abilities, it is easy to assume this is true of all students. Students who are not comfortable with technology and computers would be at a disadvantage if advised to enroll in a hybrid or online class. Advisors should be sure to ascertain a student's level of comfort with technology before suggesting that student to take a class where computer skills are essential to success. This could be accomplished through formal means, such as a computer skills placement test, or by less formal means, such as asking the student about their computer experience and level of comfort with technology.

Although not directly related to the research questions, the data from this study show that developmental math students are able to perform well in online and hybrid courses. Table 3 on page 51 shows that in both courses online students had the highest average final examination scores, hybrid students had the second highest, and traditional students had the lowest average scores. This was not a focus of analysis in this study, but it does at least support the idea that some developmental math students will thrive in online and hybrid courses. Educators should provide courses in a variety of formats to accommodate the varied learning styles and preferences of developmental math students. It also indicates the importance of further research to find the best predictors of success for these students in each delivery mode.

Implications for Administrators

This study has shown that mathematics self-efficacy is a valid predictor of success as measured by academic achievement for developmental mathematics students. Administrators may wish to institute policies that make measurement of MSE a follow-up to the placement process when students test into developmental mathematics. Counselors and advisors could be trained to interpret the results of the MSE instrument and use them in advising students.

A significant finding of this study not directly related to the research questions is how well the adapted MSE survey instrument worked. The original instrument, Nielsen and Moore's (2003) Mathematics Self-Efficacy Survey, used broad items based on general high school mathematics skills. The adapted instrument used in this study focused directly on the learning outcomes for each of the two math courses studied. As discussed earlier, the internal reliability and correlation between the subscales for the adapted instrument were virtually the same as for the original. This should encourage administrators to create MSE instruments based on the particular courses and learning environments present in their own institutions. Individualized MSE instruments should provide the best insight into the MSE and associated success potential for students at each college. Of course, such instruments should be tested and monitored for reliability and validity.

Another finding useful to administrators is the ability to predict final exam scores based on MSE measurements. The predictor equations in this study are limited to the term and institution where they were developed, but administrators could develop their own models by tracking MSE scores and final examination scores over time at their particular institution. A predicted final examination score could be provided to advisors and instructors. This would serve as an early warning that students with low predicted scores should be offered additional help and resources from the beginning of the course. It would allow for preventative measures to be taken before the student begins to struggle, record low grades, and fall behind.

Implications for the Conceptual Framework

The findings of this study have implications for the theories that formed the conceptual framework. The self-efficacy aspect of Social Cognitive Theory would imply that self-efficacy is a good predictor of achievement. In this study MSE was a predictor of success but TSE was not. Bandura (1986) stated that self-efficacy must be measured for a specific task. This study sought to measure students' self-efficacy for learning math using computers through measuring both TSE and MSE. This approach did not succeed. As mentioned earlier, the way the survey was deployed may have affected the TSE data. However, perhaps what is needed is a new instrument that combines technology and math self-efficacy in order to be truly task specific. That is, it may be that confidence in ability to use computers and confidence in ability to learn math are not equivalent to confidence in the ability to learn math using computers. Because math is the major task involved in any class format, MSE was a good predictor for the group as the theory would suggest.

When the data were analyzed by class format, MSE was only a good predictor for hybrid students although theoretically it should have been a good predictor for each group. As mentioned earlier, the small number of online students may have been why the model did not reach significance for that group. It is less certain why the results for traditional students, the largest group, were not significant. As mentioned before, hybrid students were most similar to the large group in demographics; this may be a factor. More likely, variations in pedagogies among instructors of traditional classes may have caused larger variations in final examination results. Because hybrid classes all used the same software, variations in pedagogy were probably smaller for this group. Unfortunately, no data are available to determine if such variations were even the issue. In any case, the results do not challenge the theory but rather call for further examinations of what factors may have been in place for the traditional group and the online group.

The other major theory that informed the conceptual framework was Anderson's (2008) online learning theory. The mean scores on the final examinations were highest for the online and hybrid groups. The success of these students supports Anderson's theory that online learning is valid and shows that students can succeed in online and hybrid environments.

Limitations

This study was subject to the following limitations:

1. The study used a limited sample and convenience sampling. The sample may not be representative of all developmental mathematics students in all community colleges. External validity is limited. However, similar institutions may find the results useful.
2. The study examined only two courses during one semester which may limit the ability to generalize results, even within the institution studied. Internal validity may be limited. Research across multiple institutions and semesters would strengthen the findings.
3. Of the many variables that could relate to success for community college developmental mathematics students in online, hybrid, and seated environments, this study focused on only two. One of these did not prove to be a valid predictor of success based on this specific data set. Further research is needed in this area, as discussed below.
4. Although the intent of the study was to be predictive, data were taken after students had selected a delivery mode and begun the semester. This limits the predictive power of the findings. However, this limitation was compensated for as much as possible.
5. The original validated MSES instrument was modified for this study. This was compensated for by having the developmental mathematics department provide an expert review of the modified instrument and by calculating internal reliability using Cronbach's alpha based on the responses to the revised instrument.

Recommendations for Future Research

The literature review surfaced many factors that may predict success for community college developmental mathematics students in hybrid, online, and seated environments. This study focused on technology self-efficacy and mathematics self-efficacy as a promising set of predictors. However, the findings show that TSE was not a useful predictor and MSE was not a powerful predictor in this case. The design of this study could be strengthened and improved for application in further research.

A redesigned version of this study without some of its limitations in scope and methods of data collection would offer valuable insights. Such a study should use a larger sample size, across multiple semesters, and across multiple institutions of various sizes. The survey instruments should be administered as part of the placement or advising process before the semester begins. Students should be given the opportunity to take a pencil and paper version of the survey so those not comfortable with technology have a better opportunity to participate.

A modified form of the study may also offer new insights. The inclusion of other cognitive and/or affective factors as independent variables may produce a more powerful predictive model of student success. The addition of qualitative factors such as observations and interviews in a mixed methods approach would also offer new insights into the question of what predicts success for developmental mathematics students.

Conclusion

Online and hybrid courses, which were a novelty only a few years ago, have become part of the standard offerings of community colleges. They offer qualified students both flexibility in scheduling and options in choosing a delivery mode that suits their learning preferences. It is therefore important for educators to be able to correctly advise students about which delivery mode would be most likely to enhance learning and lead to success. Developmental students, a group research has shown to have particular learning needs, are particularly in need of the best possible advice when choosing a course delivery format.

The present study has examined the ability of two potential factors related to success, technology self-efficacy and mathematics self-efficacy, to predict academic achievement for developmental mathematics students in hybrid, online, and seated environments. Although TSE did not prove to be useful predictor in the study, limitations in the way the data were taken may have affected that result. MSE, however, was shown to be significant despite those limitations. The study shows a measurement of MSE offers students and educators important information about potential success that can be a factor in choosing the best delivery mode for each student. The information from the study can also assist community college administrators in making decisions and implementing polices that will offer developmental mathematics students the best chances for success.

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Appendix A: Permission from the College to Conduct the Study

Gaston College
Opportunities for Life

Office of the Vice President

Letter of Agreement

August 24, 2011

To the Appalachian Institutional Review Board (IRB):

I am familiar with George Hendricks' research project entitled Predictors of Success for Developmental Mathematics Students in Online, Hybrid and Traditional Courses. I understand Gaston College's involvement to be conducting an online survey of developmental math students and providing data from the survey to Mr. Hendricks, as well as providing data on final examination scores for these students.

As the research team conducts this research project I understand and agree that:

- This research will be carried out following sound ethical principles and that it has been approved by the IRB at Appalachian State University.
- Employee participation in this project is strictly voluntary and not a condition of employment at Gaston College. There are no contingencies for employees who choose to participate or decline to participate in this project. There will be no adverse employment consequences as a result of an employee's participation in this study.
- To the extent confidentiality may be protected under State or Federal law, the data collected will remain confidential, as described in the protocol. The name of our agency or institution will be reported in the results of the study.

Therefore, as a representative of Gaston College, I agree that George Hendricks' research project may be conducted at our agency/institution, and that Mr. Hendricks may assure participants that they may participate in surveys and provide responsive information without adverse employment consequences.

Sincerely,

Don Ammons

Don Ammons, Ph.D.
Vice President for Academic Affairs

Appendix B: Agreement with Developmental Mathematics Department to Conduct the Study

Letter of Agreement

August 24, 2011

To the Appalachian Institutional Review Board (IRB):

I am familiar with George Hendricks' research project entitled Predictors of Success for Developmental Mathematics Students in Online, Hybrid and Traditional Courses. I understand Gaston College's involvement to be conducting an online survey of developmental math students and providing data from the survey to Mr. Hendricks, as well as providing data on final examination scores for these students.

As the research team conducts this research project I understand and agree that:

- This research will be carried out following sound ethical principles and that it has been approved by the IRB at Appalachian State University.
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- To the extent confidentiality may be protected under State or Federal law, the data collected will remain confidential, as described in the protocol. The name of our agency or institution will be reported in the results of the study.

Therefore, as a representative of Gaston College, I agree that George Hendricks' research project may be conducted at our agency/institution, and that Mr. Hendricks may assure participants that they may participate in surveys and provide responsive information without adverse employment consequences.

Sincerely,

Cherry Deal

Cherry Deal
Chair, Developmental Education

Appendix C: Permission from Institutional Review Board to Conduct the Study

IRB Notice

1 message

IRB <irb@appstate.edu> **Thu, Sep 1, 2011 at 3:37 PM**
To: hendricksgh@email.appstate.edu
Cc: bonhambs@appstate.edu

To: George Hendricks

CAMPUS MAIL

From: Robin Tyndall, Institutional Review Board
Date: 9/01/2011
RE: Notice of IRB Exemption
Study #: 12-0039

Study Title: Predictors of Success for Developmental Mathematics Students in Online, Hybrid, and Traditional Courses
Exemption Category: (1) Normal Educational Practices and Settings

This submission has been reviewed by the IRB Office and was determined to be exempt from further review according to the regulatory category cited above under 45 CFR 46.101(b). Should you change any aspect of the proposal, you must contact the IRB before implementing the changes to make sure the exempt status continues to apply. Otherwise, you do not need to request an annual renewal of IRB approval. Please notify the IRB Office when you have completed the study.

Best wishes with your research!

CC:
Barbara Bonham, Leadership And Edu Studies

Appendix D: MAT 070 Survey Instrument

Predicting Success in Developmental Math Courses - MAT 070

1. Developmental Math Course Success - MAT 070

Dear Student,

Gaston College is conducting this survey to determine factors that predict success in developmental math courses. Your help and participation are needed. You are being asked to complete a short survey (a total of 60 questions) about yourself. The survey takes about 10 minutes to complete.

While you need to provide your college student ID to complete this survey, this information will only be used to evaluate survey results and will not be used to identify your participation in any way. Your responses and all data will remain confidential.Please note your survey responses will not be usable if you do not provide a valid student ID.

If you choose not to participate in the study, there will be no penalty and it will not affect your grade in any way. If you wish to see the results of the study, email hendricks.george@gaston.edu and you will be sent an electronic copy when the study is complete.

To encourage participation, a drawing will be held when the survey is complete and one survey responder will be awarded a $100 Visa gift card. To be eligible, you must submit the survey and (a) provide your student ID number (b) be enrolled in MAT 070 or MAT 080 at Gaston College during the Fall 2011 semester. The winner will be contacted using contact information in his or her college records.You may only submit the survey once. All participants who submit the survey will have an equal chance of winning.

By submitting this survey, you are volunteering to participate in the study.

Data from this survey will analyzed as part of a doctoral dissertation for Appalachian State University. If you have questions please contact:

George Hendricks (hendricks.george@gaston.edu), Researcher
Dr. Barbara Bonham (bonhambs@appstate.edu), Faculty Advisor

Thank you for helping us improve developmental math at Gaston College!

Predicting Success in Developmental Math Courses - MAT 070

2. Student Information

Please answer the following questions.

***1. Please provide your student ID. Your ID will not be used to personally identify you in any way.**

***2. Do you wish to participate in the drawing for the $100 Visa gift card? By choosing yes, you grant permission to look up your contact data based on your Student ID number if (and only if) you win.**

- ○ Yes
- ○ No

***3. What is your gender?**

- ○ Female
- ○ Male

***4. What is your race or ethnicity?**

- ○ American Indian or Alaska Native
- ○ Asian
- ○ Black/African American
- ○ Hispanic/Latino
- ○ Pacific Islander
- ○ White/Caucasian
- ○ Other

***5. What is your age?**

- ○ Younger than 25 years of age
- ○ 25 years of age of age or older

***6. Are you married?**

- ○ No
- ○ Yes

Predicting Success in Developmental Math Courses - MAT 070

***7. How many hours do you work each week outside the home, on an average?**

- ◯ 0
- ◯ 1-10
- ◯ 11-20
- ◯ 21-30
- ◯ 31-39
- ◯ 40 or more

***8. Do you have children or other family members who depend upon you for support?**

- ◯ No
- ◯ Yes

***9. How many semester hours are you enrolled in this semester (including this course)?**

- ◯ 4-11
- ◯ 12 or more

***10. How long has it been since you last completed a college course?**

- ◯ This is my first semester in college
- ◯ Last semester
- ◯ Within the last year
- ◯ 1-5 years ago
- ◯ 6 or more years ago

***11. Have you taken an online course before this term?**

- ◯ Yes
- ◯ No

***12. Have you taken a college developmental math course before this term?**

- ◯ Yes
- ◯ No

Predicting Success in Developmental Math Courses - MAT 070

3. Technology

Please indicate how confident you felt at the BEGINNING of this semester using computer/internet technologies in an online class (even if you are not taking an online class). If you do not understand a statement, please choose "Not Confident At All".

***1. Opening a web browser**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***2. Reading text from a web site**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***3. Clicking on a link to visit a specific web site**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***4. Accessing a specific web site by typing the address (URL)**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***5. Bookmarking a web site**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***6. Printing out a web site**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***7. Conducting an internet search using one or more keywords**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***8. Downloading (saving) an image from a web site to a local disk (hard drive)**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***9. Copying a block of text from a web site and pasting it to a document in a word processor**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***10. Providing a nickname within a chat room**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***11. Reading messages from one or more members of a chat room**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

Predicting Success in Developmental Math Courses - MAT 070

***12. Answering a message or providing my own message in a chat room**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***13. Interacting privately with one member of a chat room**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***14. Logging on and off an e-mail system**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***15. Sending an e-mail message to a specific person**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***16. Sending an e-mail message to more than one person at the same time**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***17. Replying to an e-mail message**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***18. Forwarding an e-mail message**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***19. Deleting messages received via e-mail**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***20. Creating an email address book**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***21. Saving a file attached to an e-mail message to a local disk and then viewing the contents of that file**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***22. Attaching a file (image or text) to an e-mail message and then sending it off**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***23. Signing on and off of an educational learning system such as Blackboard or Course Compass**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

***24. Posting a new message (creating a new thread) to a discussion board**

○ Very Confident ○ Somewhat Confident ○ Not Very Confident ○ Not Confident At All

Predicting Success in Developmental Math Courses - MAT 070

***25. Reading a message posted on a discussion board**

◯ Very Confident ◯ Somewhat Confident ◯ Not Very Confident ◯ Not Confident At All

***26. Replying to a message posted on a discussion board**

◯ Very Confident ◯ Somewhat Confident ◯ Not Very Confident ◯ Not Confident At All

***27. Downloading a file from an educational learning system such as Blackboard or Course Compass to a local disk**

◯ Very Confident ◯ Somewhat Confident ◯ Not Very Confident ◯ Not Confident At All

***28. Uploading a file to an educational learning system such as Blackboard or Course Compass from a local disk**

◯ Very Confident ◯ Somewhat Confident ◯ Not Very Confident ◯ Not Confident At All

Predicting Success in Developmental Math Courses - MAT 070

4. Mathematics - Classroom

These questions ask you to estimate your own mathematics ability.

The questions refer to a general problem of the type indicated; assume you would be given enough information to solve the problem.

How confident are you that you can successfully perform the following tasks in a math classroom environment?

***1. Solve a problem involving signed numbers**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***2. Work a problem involving exponents**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very confident ○ Not Confident at All

***3. Solve a problem by correctly using order of operations**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***4. Simplify an expression**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***5. Solve a linear equation or inequality**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***6. Graph an equation**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***7. Solve a problem using a formula**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***8. Solve a problem involving polynomials**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***9. Factor an expression**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

Predicting Success in Developmental Math Courses - MAT 070

***10. Solve a geometry problem**

◯ Very Confident ◯ Somewhat Confident ◯ Neutral ◯ Not very Confident ◯ Not Confident at All

Predicting Success in Developmental Math Courses - MAT 070

5. Mathematics - Math Test

These questions ask you to estimate your own mathematics ability under conditions of a math test.

The questions refer to a general problem of the type indicated; assume you would be given enough information to solve the problem.

How confident are you that you could successfully perform the following tasks on a math test?

***1. Solve a problem involving signed numbers**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***2. Work a problem involving exponents**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very confident ○ Not Confident at All

***3. Solve a problem by correctly using order of operations**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***4. Simplify an expression**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***5. Solve a linear equation or inequality**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***6. Graph an equation**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***7. Solve a problem using a formula**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***8. Solve a problem involving polynomials**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***9. Factor an expression**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

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***10. Solve a geometry problem**

- ◯ Very Confident
- ◯ Somewhat Confident
- ◯ Neutral
- ◯ Not very Confident
- ◯ Not Confident at All

Appendix E: MAT 080 Survey Instrument Sections 4 and 5

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4. Mathematics - Classroom

These questions ask you to estimate your own mathematics ability.

The questions refer to a general problem of the type indicated; assume you would be given enough information to solve the problem.

How confident are you that you could successfully perform following tasks in a math classroom environment?

***1. Factor an expression**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***2. Solve a problem involving rational expressions**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***3. Work a problem involving rational exponents**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very confident ○ Not Confident at All

***4. Solve a quadratic equation**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***5. Solve a problem involving systems of equations**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***6. Solve a problem with inequalities**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***7. Solve a problem involving functions**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***8. Solve a problem involving complex numbers**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***9. Solve a geometry problem**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

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5. Mathematics - Math Test

These questions ask you to estimate your own mathematics ability under conditions of a math test.

The questions refer to a general problem of the type indicated; assume you would be given enough information to solve the problem.

How confident are you that you could successfully perform the following tasks on a math test?

***1. Factor an expression**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***2. Solve a problem involving rational expressions**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***3. Work a problem involving rational exponents**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very confident ○ Not Confident at All

***4. Solve a quadratic equation**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***5. Solve a problem involving systems of equations**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***6. Solve a problem with inequalities**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***7. Solve a problem involving functions**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***8. Solve a problem involving complex numbers**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

***9. Solve a geometry problem**

○ Very Confident ○ Somewhat Confident ○ Neutral ○ Not very Confident ○ Not Confident at All

Appendix F: Permission to Use the OTSES

From: Chong Yu <alex.yu@asu.edu>
To: George Hendricks <Hendricks.George@gaston.edu>
Date: 7/21/2011 4:39 PM
Subject: RE: Permission to use OTSES instrument

Hi, George, sorry that I overlooked this email. Yes, please feel free to use it for your research.

From: George Hendricks [Hendricks.George@gaston.edu]
Sent: Tuesday, July 12, 2011 7:16 PM
To: Chong Yu
Subject: Permission to use OTSES instrument

Dear Dr. Yu,

I am a doctoral student at Appalachian State University in Boone, North Carolina. I am working on my dissertation "Predictors of Success for Community College Developmental Mathematics Students in Traditional, Hybrid and Online Courses."

I am requesting permission to use the Online Technologies Self-Efficacy Scale as part of my work. I will, of course, cite your work and give you and Dr. Miltiadou credit as creators of the survey.

Thank you for your time and your important contributions to online education.

Respectfully,

George Hendricks

George Hendricks
Associate Dean of Engineering and Industrial Technologies
Gaston College
704-922-6305

"Email correspondence to and from this sender may be subject to the North Carolina Public Records law and may be disclosed to third parties."

VITA

George Harrison Hendricks, III, was born in Columbus, Georgia, on August 26, 1959. He attended public school in Columbus and in Commerce, Georgia. He graduated from Commerce High School with honors in 1977. He entered the U.S. Air Force in 1978 and earned an Associate of Applied Science in Avionics Systems Technology from the Community College of the Air Force in 1981. In 1986 he received a Bachelor of Science in Electrical Engineering from the University of New Mexico and graduated from Air Force Officer Training School. He earned a Master of Engineering in Electrical Engineering from the University of Florida in 1992. He left the Air Force that year and began work as a manufacturing engineer for a large electrical motor manufacturer in Kings Mountain, North Carolina. In 2000 he accepted a position at Gaston College in Dallas, North Carolina as chair/instructor in the Electronics Engineering Technology Department. He received an Education Specialist degree in Higher Education Administration in 2006 and a Doctor of Education degree in Educational Leadership in 2012 from Appalachian State University.

Dr. Hendricks currently serves as the Associate Dean of Engineering and Industrial Technologies as well as an instructor in the Electronics Engineering Technology department at Gaston College. He lives in Shelby, North Carolina, and is married to Vicki Hendricks. They have three children and seven grandchildren.