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Effect of Technology on Community College Developmental Mathematics Course Completion Rates

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This is to certify that the doctoral study by

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has been found to be complete and satisfactory in all respects,
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Walden University
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Abstract

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MA, Walden University, 2007

BA, Morningside College, 2001

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

Students who enter community colleges in need of developmental education are often at high risk of failure due to identities or perceptions of self, that do not conform to college expectations that can be problematized by age, gender, and ethnicity. Additionally, students' efficacy for using technology may affect completion rates which was examined at Midwest Community College (MCC) through observing a program shifting from teacher-directed course designs with greater teacher–student interaction to technology-directed course designs with greater technology–student interactions. The theoretical foundation of this study was Tinto's theory of student retention based on the belief that student success is facilitated by internalizing a student identity. The research questions were focused on a comparison of student course completion rates between teacher-directed mathematics courses (teacher DMC) and technology-directed mathematics courses (technology DMC). Using logistic regression in a quantitative quasi-experimental design, course completion rates were regressed on course design type, age, gender, and ethnicity for 2,900 students at MCC after a shift from teacher DMC to technology DMC. Key findings showed that technology DMC had a statistically significant effect on completion rates at the .01 significance level. When combined with technology, age had a statistically significant effect on completion rates (.001), but not ethnicity or gender. The results suggest that technology DMC have the potential to improve student retention in developmental education programs and elicit positive social change. This change may positively impact college graduation rates, as it provides support for developmental education programs that can help students complete college.

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Dedication

This dissertation is dedicated to my family. To my mother, all of my strength and desire to achieve great things comes from you. To my daughters, the reasons why I refuse to fail.

Acknowledgments

I would like to extend my thanks to the following people who made it possible for me to complete this journey: Dr. Markus Berndt, for guiding and challenging me throughout the process, Dr. Anita Dutrow and the Dr. Beate Baltes for also providing guidance, and Michael Cagley who helped me achieve my goals.

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Chapter 1: Introduction to the Study

This study is focused on developmental education mathematics courses in community colleges with teacher-directed mathematics courses (teacher DMC) compared to technology-directed mathematics courses (technology DMC). In the technology DMC, students have more flexibility in both learning material and completing homework. Students use individualized academic software and online tools, such as Assessment and Learning in Knowledge Spaces (ALEKS), that adjust to a student's level of mathematical skill proficiency to best build on the skill sets present and facilitate the improvement of the deficient skill sets. Individualized learning in ALEKS may be more effective than traditional teacher–student interactions directed at a classroom full of students who are assumed to be at a level of proficiency for lessons.

At Midwest Community College (MCC), courses using ALEKS continue to meet in brick-and-mortar classrooms on a schedule consistent with teacher-directed learning, but each student proceeds through material guided by ALEKS rather than the teacher. In this design, the teacher can address problem areas for students using the online monitoring of student progress and answer in-class questions, but all testing, homework, and course grades are in the hands of the ALEKS software. All the tests and homework, moreover, can be completed outside of the classroom at the students' convenience. To get leverage on whether technology DMC can be a more effective class design than teacher DMC, a community college identified by MCC was chosen for this research. MCC's administration agreed to provide quantitative data on completion rates and other relevant variables under study, with the data encompassing the time during which MCC shifted from teacher DMC to technology DMC in its developmental education program.

In 2013, MCC revamped developmental mathematics courses to address the problem of course completion. One of the reasons that they chose to use computerized instruction as the primary method of redesign was a state-wide initiative to include mathematics software in certain mathematics courses. Further, MCC received a federal grant to redesign mathematics courses using technology. MCC collected data over the course of 3 years from a 16-week teacher DMC and the technology DMC, which included self-paced, computerized independent learning. The data include course completion status (pass or no-pass) from both the teacher DMC and the technology DMC and learner demographic information including age, gender, and ethnicity. Thus, not only is this study focused on this independent variable in terms of its effect on completion rates in the courses in addition to the dependent variable, but this study also incorporates key predictor variables in accord with research on education: age, gender, and ethnicity.

Chapter 1 of this study provides an overview of the research. The introduction details the history of developmental mathematics' learners at MCC. MCC introduced technology DMC in the developmental education mathematics program to try to improve completion rates, which provided an ideal opportunity to study the effect of technology on completion rates. The background section provides national data regarding the developmental education epidemic and the importance of this study. The next section includes the problem statement, followed by the purpose of this study, which helps to better frame the research questions in the quasi-experimental design. Finally, Chapter 1 will end with a summary and a brief overview of Chapter 2.

Background

According to the Center for Community College Engagement (2016), nationally almost 70% of students, or approximately 1.5 million, who leave high school and enter college are placed into developmental education courses. King, McIntosh, and Bell-Ellwanger (2017) reported that during their first few years of education, 59% of community college students overall will need some developmental math course, compared to approximately half that value for developmental English at 28% (p. 5). These numbers represent serious issues in education because the total community college student population is over 9 million students, meaning that over 6 million students enter college unprepared (Community College Research Center, 2017). This issue is highlighted through data on the completion rates of students from 57 community colleges across 10 states:

- 59% of community college students were referred to developmental education mathematics.
- 24% of the 59% were referred to a single class only.
- 16% of the 59% were referred to a sequence of two courses.
- 19% of the 59% were referred to a sequence of three courses.
- Within a 3-year time span, only 20% of the 59% of the student body referred to developmental math completed their courses and passed a college-level math course (Jaggars, Hodara, Cho, & Xu, 2015).

Although there is a demonstrated need for development education based on the meta-analysis of research by the Center for Community College Engagement (2016), few students complete their developmental courses even though over two-thirds of high school students entering community colleges end up being placed in developmental education courses; even in terms of the 1.7 million annual new first-year community college students, approximately 60% of each new cohort must take one or more developmental math course (Hoang, Huang, Sulcer, & Yesilyurt, 2017). However, only 11% of students who are referred to three or more developmental mathematics courses complete those courses and pass the gatekeeper mathematics course (Bailey & Jaggers, 2016). Completion rates are even worse in the lowest level of developmental mathematics courses with only 8% of students completing a college-level course (Bailey, Jaggars, & Jenkins, 2015). Contrary to popular opinion, the problem of underprepared students is not a new one (Arendale & Bonham, 2014). Boylan and White (2014) posited that the United States has offered some sort of developmental education since the beginning of its nation's history. The demographics of the students who are placed into developmental courses vary and represent a cross-section of the population, though Dasinger (2013) maintained that younger students are more apt to complete developmental education courses than are nontraditional students.

Despite the need for developmental education courses, completion rates for courses may still not improve. According to a study by the Community College Resource Center researchers, students who were enrolled in developmental education courses typically did no better in course completion than students who did not take developmental education courses and were enrolled in college level classes (Scott-Clayton, Crosta, & Belfield, 2012). The researchers maintained that nearly 70% of students in developmental education courses would have passed a college-level mathematics course without the developmental course (Scott-Clayton et al., 2012).

Although much has been written about the problem of student completion in developmental education courses, a gap still exists in practice when determining what types of courses, whether traditional lecture-based courses or technology DMC courses that include self-paced computer-based learning, are best suited to the learner dependent on demographics (Booth et al., 2014). In other words, evaluation of the benefit each learner may derive from course types may be related to demographic data such as age, gender, and ethnicity (Booth et al., 2014). Therefore, there may be factors that together complicate success for students in developmental education mathematics courses.

Problem Statement

There is a high failure rate of MCC students in the DMC. Annually, a little over 6,000 students are enrolled at MCC, of which about half are first-time students. In 2012, 84% of those entering the college, or about 2,500 students, did not have the required skills in mathematics to enroll in their desired programs to earn a certification or to enroll in the appropriate college-level mathematics for an associate's degree; therefore, MCC's academic guidance staff directed these students to begin with developmental mathematics education. According to an office for MCC, the percentages of students whose placement scores indicated a need for mathematics skill development for college coursework was 79.4% in fall 2010, 82% in fall 2011, and 84% in fall 2012.

Of the MCC students who were determined to need developmental math courses, 432 students demonstrated a need for serious math skill development at the entry level of arithmetic to even prepare them for entry into algebra, geometry, and eventually into college mathematics. The other students proceeded through different levels of developmental mathematics toward their goals, but the current study was focused on the students needing the most fundamental math skill developments like the 432 students. Moreover, 42.6% or 184 students, passed the fundamental math skill development course while 248 students did not. Even after passing this course, the 184 students would be expected to proceed through other developmental math classes, which usually means at least one more math course until achieving the level of aptitude necessary to enter college algebra or a specific program. Therefore, early success can be crucial for students to develop successful student identities, especially for those struggling in fundamental math courses because these students will face at least one more math class. This research was focused on these students at the most fundamental level of development.

The problem at MCC is consistent with community colleges nationwide according to a meta-analysis of research on community colleges in the United States reported by the Center for Community College Student Engagement (2016); developmental education may need a complete overhaul and redesign of courses due to the low pass rate in developmental mathematics. Traditional methods of teaching and delivery may not lead to course completion; therefore, institutions of higher education are working to develop new ways of delivering remediation in mathematics. For instance, Kosiewicz, Ngo, and Fong (2016) maintained that courses that were traditionally semester-long and lecture-based often increased the likelihood that a student would spend much more time in college and many times drop out without having completed a degree. Therefore, it is important to explore the potential benefits of a technology emphasis in development education, which will be addressed in this study.

There are many factors that may contribute to the high failure rate among students who take developmental mathematics classes such as whether the appropriate student support services have been implemented, including both academic supports like tutoring and personal supports like career counseling; whether faculty have been appropriately trained with long-term faculty development focused on the needs of developmental education learners; and whether the material is of an appropriate level of rigor to propel students into their educational trajectories rather than posing an obstacle (Jaggars et al., 2015). In this study, I examined the rigor or academic content of a technology DMC that includes independent, computerized learning in a self-paced environment, using the predictor variables of age, gender, and ethnicity. Thus, this study extends research findings that showed self-paced and alternative course designs may have better overall completion rates and outcomes than other courses but did not compare traditional classrooms with greater emphasis on teacher-directed learning to classrooms with greater emphasis on technology DMC in conjunction with the variables of age, gender, and ethnicity.

Gender has been researched in terms of possible stereotype threat in mathematics, especially since the 1990s with researchers such as Steele (1997) and Spencer (see Spencer, Steele, & Quinn, 1999). The effects can begin in adolescence and persist into adulthood (Good, Aronson, & Inzlicht, 2003). Moreover, stereotype threat has been extended to ethnicity, especially in college and college testing (Aronson & Inzlicht, 2004; Aronson et al., 2002; Steele, 1997; Steele & Aronson, 1995). Additionally, age and ethnicity may have connections to underdeveloped abilities in a classroom with technology prioritized over a teacher, the traditional classroom. In urban secondary schools, as Kozol (2005; 1991) has documented, ethnicity plays a role in funding problems as well that can create issues in the quality of education. Stereotype threat remains a relevant research issue along lines of ethnicity and gender in education from K-12 to college, as a review of stereotype threat research indicates (Spencer, Logel, & Davies, 2016). Another indirectly investigated aspect of this research, then, is the possibility of technology playing a more neutral or less-biased role in learner education, which may provide justification for further research into potential teacher biases and appropriate faculty development programs to raise awareness of such biases to reduce or eliminate them.

Finding the best developmental education course designs to facilitate student completion rates also has financial benefits to students, though this study was primarily focused on the potential connections between academic integration in terms of success in courses. The number of students needing at least one developmental course is estimated at 1.7 million (Fulton, Gianneschi, Blanco, & DeMaria, 2014); however, few developmental education students graduate with a certificate, diploma, or degree (Scott-Clayton et al., 2012). Low DMC completion rates nationwide have led to serious discussions about an overhaul of developmental education and a redesign of courses, according to a meta-analysis of research published by the Center for Community College Engagement (2016). Some community colleges are looking at eliminating developmental education courses completely (Saxon & Morante, 2014) and placing students directly into college-level courses. Many colleges have put accelerated programs into place to address outside factors that influence completion of the developmental education sequence (Jaggars et al., 2015). Students placed in accelerated models can also finish the course in less time than the standard semester (Cafarella, 2016b).

In sum, though educational experts identify low completion rates across the nation in DMC, there are no identifiable solutions. One key focus of evaluating the most effective DMC designs centers on whether a teacher's active and persistent presence in the classroom accomplishes more for course completion rates in the course than a course focused on technology. This question sets the stage for further evaluation of teacher leadership best practices in relationship to technology. In other words, it is possible that students who may feel marginalized in some courses due to stereotype threat could perform better when technology is emphasized and available at their convenience, which may imply that human instructors bring biases into classrooms or that the students interpret biases in the instructors' actions. The variables gender and ethnicity give some degree of insight into this possibility, with insights perhaps strengthened with the inclusion of age. Therefore, this research examines the effect of technology implementation on DMC completion rates at MCC, with additional predictor variables included to try to find further insights into viable solutions for the widespread low completion rates.

Purpose of the Study

The purpose of this quantitative study was to compare completion rates in DMC of over 2,900 MCC students in teacher DMC and technology DMC. Although the primary independent variable is course design type and its effects on the dependent variable of completion rates, additional independent variables of age, gender, and ethnicity could provide additional insight. In other words, MCC and other institutions like it could benefit from statistical data that demonstrate whether the technology DMC have improved student completion rates in DMC. Per Tinto's framework, students who experience success early in their educational trajectories should integrate into the institutional culture and educational culture overall, reinforcing their sense of belonging within the institution and postsecondary education in general (see Figure 1).

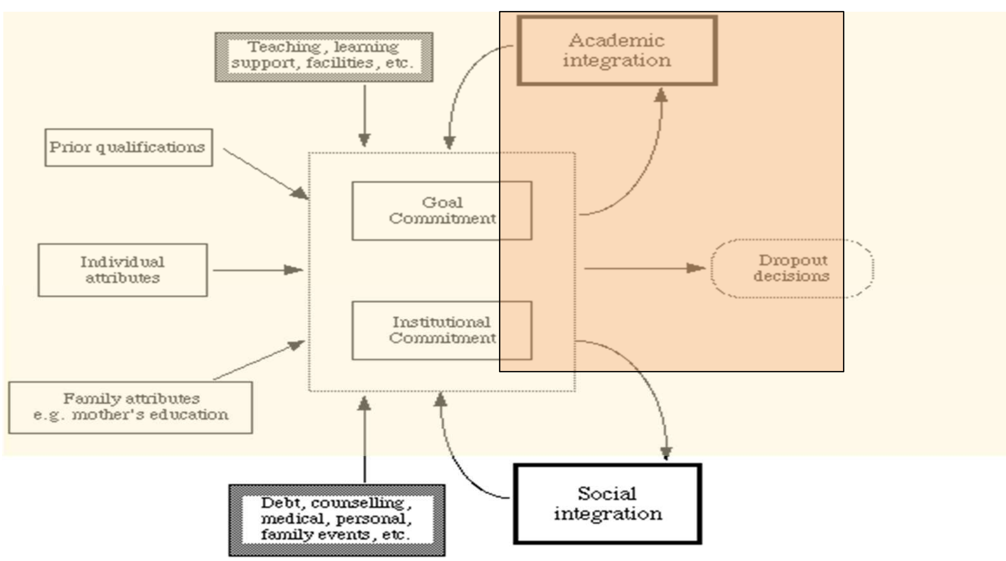

Figure 1. Tinto's theory of student retention. From "Tinto's model of student retention," by S. W. Draper, 2008. Retrieved from http://www.psy.gla.ac.uk/~steve/localed/tinto.html

In the figure, the upper portion of the figure has been highlighted in two shades. The broad shading across the entire upper portion captures the student's immediate interaction in the academic setting focused on academic merit. It can also be the aspect of student integration over which the student has the most direct control, with academic integration, or success in the classroom and the more darkly highlighted smaller box in Figure 1, becoming a cyclical reinforcing experience in repeated iterations. The same could be stated for repeated failures or struggles in that alienate the student from the academic setting in repeated iterations. The lower half of the figure, generally connected more broadly to social integration, goes beyond the purview of this research in the holistic theory proposed by Tinto. This research was focused on academic integration in the form of student success or lack thereof in DMC, students who can be considered high risk in terms of acculturating to postsecondary education, with the primary focus on technology's effects on completion rates. The additional variables are included because stereotype threat and technology literacy may be further complicating students' attempts to gain momentum in iterations of academic integration.

Therefore, it is also important to examine the possible effects of age, gender, and ethnicity on developmental education mathematics course completion rates, because integration into the institutional culture and educational culture in general cannot occur without student success in the classroom. Moreover, the data provide an opportunity to conduct statistical tests using logistic regression correlation tests with the population functioning as a sample of Midwest adult students in development education from 2010 to 2015, with the sample treated like pooled panel data in a quasi-experimental design.

The population data used as a sample in a quasi-experimental design allows for the suggestion that relationships may exist between the added independent variables; however, the relationships may include covariance in line with research on intersectionality (Collins & Bilge, 2016). Although the gender and age distributions of MCC are similar to both Midwest region and national community college demographics, MCC is more diverse in general in terms of ethnicity. According to research by the Kaiser Family Foundation (2017), MCC has a student body population more diverse than both the state average and the regional average of the Midwest, with the percentage of White students at MCC at 63%, near the national average of 61%. Thus, if used as a convenience sample, the developmental education mathematics students at MCC would be nearly as diverse as the average community college nationally, allowing for an assumption of oversampling of nonwhite students. Although these variables are of more interest to future research designs regarding tests of stereotype threat and age-related technology literacy in relationship to technology, the completion rates as they relate to the introduction of the technology DMC are important to MCC due to student outcomes in the development education mathematics.

Research Questions and Hypotheses

This quasi-experimental study has three research questions with the teacher DMC treated as the control group and the technology DMC treated as the experimental group. There is a total of three primary research questions. The first question is a basic question of whether a teacher’s active and persistent presence in the classroom accomplishes more for course completion rates in the course than technology with individualized lessons, evaluations, and tests. This question sets the stage for further evaluation of teacher leadership best practices. Thus, additional research questions address whether age, gender, and ethnicity each have effects. The logistic regression models were used to examine combinations of the variables for interaction effects: age and gender, gender and ethnicity, and age and ethnicity. Finally, the last question probes whether all the variables interact together or individually influence completion rates in courses based on teacher interactions.

RQ1: What is the difference in student course completion rates between teacher DMC and technology DMC at MCC?

$H_1$1: There is a significant difference in student course completion rates between teacher DMC and technology DMC.

$H_0$1: There is no significant difference in student course completion rates in teacher DMC and technology DMC.

RQ2: What is the difference in student course completion rates between teacher DMC and technology DMC at MCC when controlling for age?

$H_1$2: There is a significant difference in student course completion rates between teacher DMC and technology DMC when controlling for age.

$H_0$2: There is no significant difference in student course completion rates in teacher DMC and technology DMC when controlling for age.

RQ3: What is difference in student course completion rates between teacher DMC and technology DMC at MCC when controlling for gender and ethnicity?

$H_1 3$: There is a significant difference in student course completion rates between teacher DMC and technology DMC when controlling for gender and ethnicity.

H_0: There is no significant difference in student course completion rates between teacher DMC and technology DMC when controlling for gender and ethnicity.

Theoretical Framework for the Study

The theoretical framework for this quasi-experimental quantitative study was Tinto's (1975) model of student retention. With the desire for community colleges to develop better practices for improving student completion rates, researchers have studied outcomes related to this study's focus on student retention. Instructors have been found to have effects on student completion rates due to the instructor's level of education, instructor's status as full time or part time, and instructor's teaching experience (Chingos 2016). Quarles and Davis (2017) also found that the type of mathematics being taught by instructors, whether procedural or conceptual, has effects on outcomes for students not only in completion but also in ability to engage and succeed in higher level mathematics courses over the course of a student's education. Booth et al. (2014) compared various alternative course designs and found that self-paced designs, with varying levels of instructor and technological interaction, tend to have better outcomes for students. Most recent research on developmental education course designs suggests that completion rates and perhaps overall success in college may depend on institutional structure, instructor practices, and innovate uses of technology for self-paced learning. The data available for the research allow for an examination of classes with greater instructor interaction in comparison to classes with greater technology interaction.

In addition to factors affecting completion rates regarding instructors, recent research identifies possible effects of age-related issues in technology literacy, which may lead to complicated intersectionality effects with gender and ethnicity beginning as early as in middle school (Ritzhaupt, Liu, Dawson, & Barron, 2013). If gender and ethnicity in early years of education influence technology literacy, the effects may persist into adulthood. The problem is determining whether the issues result from inadequacies in the system in preparing students for using technology or in possible manifestations of stereotype threat in academic settings.

Stereotype threat has been studied in relationship between gender and mathematics, with researchers finding it still persists across the entire education system with questions of context specifics under greater scrutiny (Picho, Rodriguez, & Finnie, 2013). Even the College Board (2012) data indicated gender-based differences that may support stereotype threat for college-bound seniors in 2012. All these findings further suggest that stereotype threat for nonwhite students in mathematics may also be understudied at the college level because research of students in K-12 has indicated stereotype threat appears to be present for nonwhite students academically (Wasserberg, 2014). Additionally, students who were able to develop strong academic identities at an early age may be best equipped to resist stereotype threat (Wasserberg, 2014).

Tinto's framework for academic integration via perceptions of self as successful students academically was appropriate to explore areas of research seemingly understudied at the college level. It is conceivable that students who experience small yet repeated and reinforcing successes with technology in a self-paced environment may build stronger successful student identities than students in classrooms with traditional teaching strategies. Thus, one of the assumptions of this research is that a more individualized approach may be especially valuable to students struggling to find academic identities, older students who may have long periods of absence from the educational system, or students who have had highly negative experiences with the academic world in the past. Moreover, these assumptions may intersect with stereotype threat as well as technology literacy in complicating the learning experience, which may be better suited in its delivery style for those who have, for example, been out of the education system for a long period of time yet may not have the technology literacy level to benefit fully from the delivery system.

Tinto's (1975) model addresses the level of student integration in regard to the course completion rate of the student. Tinto maintained that academic integration at the college level predicts the students' completion rates. Two elements of academic integration, under the model of student retention theory, are how a student perceives what is being learned and whether a student is able to relate the learning to academic standards. Tinto's model of student retention supports the idea of using the technology DMC to provide more integration among the students enrolled in these courses (Davidson & Wilson, 2013). Tinto's model applied to this study because greater academic success and involvement, if derived from the technology DMC, should benefit students in outcomes. However, it is possible that teachers in general may provide better integration for students without technology intervening. The predictor variables may also be influencing these probabilities; for example, age might show correlations between younger students and technology and older students and teacher interaction. Chapter 2 will detail the major theoretical propositions and/or hypotheses.

Nature of the Study

The research design included binary logistic regression because the dependent variable course completion rate is a binary or dichotomous variable in the form of either pass or no pass (see Garson, 2016). Additionally, the inclusion of a continuous variable in age and possible covariance issues both provide support for using multiple logistic regression models to observe changes that may indicate some level of covariance that may not be immediately observable in VIF tests. The data were analyzed to discover statistical differences between the success rates of those groups of students who took the teacher DMC and the technology DMC when using the predictor variables of age, gender, and ethnicity. The study represents a quasi-experimental design as well because MCC's introduction of technology DMC represents a change in the independent variable to observe outcomes or effects in the dependent variable course completion rates.

In this quasi-experimental quantitative study, I compared the difference between the course completion rates of students, with the independent variables of age, gender, and ethnicity, in traditional 16-week, teacher DMC and technology DMC. The technology DMC include independent, computerized learning in a self-paced environment. Data from courses over the past 6 years were examined, including 3 years of data from traditional mathematics courses and 3 years of data from technology DMC. Success in the course was defined by course completion.

The dependent, independent, and predictor variables for the study are as follows:

- Dependent variable: Course completion rates
- Independent variable: Course design type
- Additional independent/predictor variable: Age
- Additional independent/predictor variable: Gender
- Additional independent/predictor variable: Ethnicity

The population included over 2,900 college freshmen whose college placement test scores indicated the need for remediation and were enrolled in either a traditional teacher DMC course or a technology DMC. The population of over 2,900 students were drawn from 2010-2015. All students who were enrolled in a teacher DMC or technology DMC during the years of 2010-2015 were included in the study. The population represents a biased sample of Midwest adult students in developmental education, which allows for statistical test assumptions to be applied.

Definitions

Acceleration: Acceleration in developmental education enables students to progress rapidly through a series of courses and into college-level work. These courses are often condensed into a shortened timeframe and include the use of computerized software. Various types of accelerated formats will be covered in Chapter 2 (Wladis, Offenholley, & George, 2014).

Assessment and LEarning in Knowledge Spaces (*ALEKS)*: ALEKS is a computerized, artificially intelligent assessment mathematics program. In ALEKS learners are given problems that increase in difficulty as they progress. The program can determine where a student is struggling and modify accordingly. Students can progress through all of developmental and upper-level mathematics courses using ALEKS (ALEKS, 2017).

Avoidance: In developmental education, avoidance is an approach that helps students to avoid taking developmental coursework, so they can move directly into college-level coursework. Types of avoidance will be covered in Chapter 2 (Wladis et al., 2014).

Community college: A community college is an institution accredited to award the associates of art or associates of science degree at its highest degree. Community colleges focus on strengthening the workforce and providing students with the skills to transfer to a four-year institution. A major focus of the community college is to provide access to those learners who otherwise would not have an opportunity (Iowa Department of Education, 2017).

College placement exam: The college placement exam is the entrance exam used by MCC. The test identifies deficits in student's math abilities and is used to place students in appropriate courses (College Board, 2017).

Developmental education: Developmental education is a field of practice and research within higher education with a theoretical foundation in developmental psychology and learning theory. It promotes the 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 (National Association for Developmental Education, n.d).

Developmental education courses: Developmental education courses help learners to learn a new skill or build upon a set of skills they already have. These are courses to help build on a current set of skills and emphasize transferable skills (National Association for Developmental Education, n.d.).

Developmental mathematics: Course work in mathematics that is remedial in nature and not transferrable to a 4-year college. Developmental mathematics courses do not meet college-level requirements. They are designed to prepare learners for college-level work. Developmental mathematics include:

- Operations with whole numbers and fractions; topics included in this category are addition, subtraction, multiplication, division, recognizing equivalent fractions and mixed numbers, and estimating.
- Operations with decimals and percentages; topics included in this category are addition, subtraction, multiplication and division with decimals as well as percentage problems, recognition of decimals, fractions and percentage equivalences, and problems involving estimation.

- Applications and problem solving; topics included in this category are rate, percentage, and measurement problems, simple geometry problems, and distribution of a quantity into its fractional parts (Hargens, 2013, p. 13).

Instructional relevance: A variety of approaches that make change to curriculum or modality so courses become more engaging to learners. These will be discussed further in Chapter 2 (Wladis et al., 2014).

Remedial mathematics: Courses that teach the skills necessary for students to complete college level coursework (Sparks & Malkus, 2013).

Support: Approaches that assist developmental education learners and enable them to proceed through the sequence of courses. Various types of support will be covered in Chapter 2 (Wladis et al., 2014).

Assumptions

In this study, it is assumed that the data received from MCC were accurate and complete. For the results of the study to have meaning that will impact future learners, it is vital that the data be precise. Additionally, it is assumed that the faculty implemented the technology DMC with fidelity. In other words, it is beyond the scope of this research to evaluate whether faculty managed the transition to technology DMC seamlessly without in some way affecting student completion rate outcomes. It is also assumed that there is a similar broad range of students and abilities included in each of the 6 years of the study. In other words, the skills and abilities of students in the developmental courses do not deviate from an expected range of mathematical competence across the data, as placement in the courses depends on student test scores.

Moreover, an implicit question in the research centers on what role the teacher plays in success or the lack thereof in course completion rates, with an assumption based on literature that teachers may bring biases into the classroom that affect the learning of students. This assumption is related to the self-fulfilling prophecy first explored in research by Rosenthal and Jacobson (1968), which is essentially the foundation of research focused on stereotype threat. Such a theoretical paradigm is important in a college setting with developmental learners who may experience problems with confidence, which justifies the use of a comparison between the teacher DMC and technology DMC.

Scope and Delimitations

The study was focused on data from MCC for the years 2010-2015 and include results of the teacher DMC and technology DMC only. The population, for statistical testing purposes, represents a weighted, biased sample for a case control study with the key independent variable introduced in the form of technology DMC, though independent variables are also involved. Generalization is problematized due to the nature of using statistical tests on a population treated as a biased sample. The next section includes further information on the limitations of generalizability with an emphasis on the study as a kind of pilot study for developing hypotheses that researchers could further test with true random sampling techniques.

The results of the tests can be used to develop possible hypotheses for testing research at other community colleges because the population can be treated as a biased sample of community colleges in the Midwest in a quasi-experimental pilot study. A true random sample could be drawn from the population available at the college, but then the number of cases in the technology DMC would drop in number from its current total of 400. With only 400 cases for the technology DMC courses, it is better to treat the population as a biased sample of MCC, which is why I was careful in interpreting the results of statistical tests as well as in attempts to generalize. However, treating the population as a convenience sample allows for this study to be pilot study to generate theoretical contributions to hypotheses that may be of value for true random sampling methods. The limitations of generalization are based on the statistical test assumptions associated with multiple logistic regressions.

The population can be treated as a kind of convenience sample of MCC because it is similar to “captive participants such as students in the researcher’s own institution” (Etikan, Musa, & Alkassim, 2016). Because the specifics of the technology DMC are well known at MCC and comparable course designs at other colleges may not be easy to identify, MCC offers an ideal environment for a pilot study to compare outcomes based on the course design in mathematics courses. A true random sample would be best designed to draw from the Midwest community college population overall, if the same kind or similar course designs were easily identified for random sampling to create a quasi-experimental group for comparison to the control group, to better account for geographically related cultural and/or socioeconomic differences, both in teachers and in students. A true random sample could also offset any peculiarities specific to MCC culturally or administratively. A convenience sample generates insights for future tests of hypotheses that may be supported by the results from the analyses of the convenience sample.

The population for this study, representing a weighted, biased sample, is drawn from 6 years or 12 semesters of developmental mathematics courses at MCC. The data include descriptive statistics of learners along with statistical tests of course completion rates of learners. The developmental course selected for this study is MAT 090: Basic Math. Elementary Algebra, Applied Mathematics, and Introductory Algebra, although all listed as developmental, nontransferable courses, were not be included in this study.

Limitations

This study was limited to 6 years of data based on the results of over 2,900 students. Another limitation of the study is that the data came from only one community college. Both these limitations could impact the internal validity of the study if there are internal biases. For example, incorrect data could be given that would impact the outcome of the study. The study is further limited by the confines of the technology DMC. In other words, different results could be seen should MCC have used alternative instructional or delivery methods in their technology DMC.

The hypotheses were tested with a set of binary logistic regression models. Logistic regression, as is the case with most statistical tests of significance, generally relies on an assumption of a random sample (Agresti & Finlay, 2008). The data in this study are a population, but the structure of the study is also consistent with a case control study (see Mann, 2003). Although most case control studies also assume a random sample, a biased, weighted sample can still be analyzed with binary logistic regression due to the nature of binary logistic regression (McCullagh, 2008). One concern, emphasized by McCullagh (1980, 2003), with logistic regression is always risk of covariance within independent variables, especially with ordinal data. Therefore, a purposeful, stepwise process can be used to identify any potential covariance that may indicate the need to use interaction effect variables (Bursac, Gauss, Williams, & Hosmer, 2008). Including the independent variables in steps toward the final model provides insights into potential intersectionality and covariance not observable in VIF tests prior to generating the models. Possible interpretations of goodness of fit indicators for each logistic regression model can also provide insights into the research questions in relationship to the final model.

Problems of external validity include the generalization of results of the study to other disciplines or even to other courses within developmental mathematics. In terms of generalizability, the test results are limited to adult student populations in developmental education, specifically mathematics course at MCC with potential for future research to develop hypotheses. The findings may be best suited for other Midwest community colleges initially for future research, but the findings may also be of interest in nationwide research. In terms of other disciplines, the literature review in Chapter 2 helps to situate the operationalized variables in the appropriate social science field within education.

Construct validity problems could occur if inferences are made based on the results of tests on certain variables. To avoid issues of internal validity, external validity, and construct validity concerns or biases, an independent party will verify the data presented by MCC. The limitations of binary logistic regression primarily reside in appropriate interpretation of correlates with the understanding that correlation does not equal causation. Hence, variable selection and examined relationships must be informed by literature, which is covered in the Chapter 2 literature review. Moreover, Chapter 3 addresses construct validity. However, it is worth noting that the variables under analysis are rather simple in terms of operationalization without requiring the design of any instrument scale.

The most likely threat to the research is in sample size since one group is fairly small in sample size at an estimate of 400. The smaller group is essentially the experimental group, in terms often used in social sciences though no actual experimental design accompanied the introduction of the mathematics courses at MCC. Nonetheless, most statistical modeling assumptions suggest a minimum of 50 cases per predictor (Burns & Burns, 2009). The study included four predictors, with one primary predictor in the form of the course type and three variables as other potential predictors. Thus, it should be within reasonable limits to use a sample size of 400 for the experimental group.

Significance

Tinto's (1975) theoretical framework provides a foundation from which to explore the possible intersections of variables that have been observed historically to be associated with education outcomes: gender and ethnicity. Much research in the past has focused on gender and ethnicity in K-12 education, especially as components of the broader social science category of socioeconomic status. Even education is a part of the fuller operationalizations of socioeconomic status in research. With the rise of nontraditional students—who are often identified by their advanced age when compared to traditional students directly out of high school in beginning or returning to postsecondary education due to losing jobs or seeking retraining—community colleges fulfill an important role in retraining these workers with skills for the new economy. Thus, this quasi-experimental pilot study provides a platform from which researchers can launch further studies into the complexities of course designs when age, gender, and ethnicity are also introduced as possible predictor variables of outcomes.

This study contributes to making sure that colleges are preparing adults to be ready to enter the work force with the skills and knowledge they need to be successful. Identifying the most effective course designs for developmental education mathematics learners will allow students to move on to regular college coursework more rapidly, thus decreasing the amount of time before they enter the work force. These outcomes can be seen as significant pragmatic outcomes for the community colleges and their student populations overall.

The potential implications for positive social change center on the potential for developing teacher awareness training programs at MCC if human biases seem evident, evaluating the role of technology for students overall, exploring the role of technology in age-related technology competence, and exploring the role of technology in its relationship to stereotype threat. For example, consider a possible relationship between age and outcomes within the two different mathematics course types. If younger students have better completion rates in technology DNC while older students, or generally nontraditional students per the definition used in this study, have better completion rates in teacher DMC, the statistical tests of the data may suggest hybrid learning environments that account for cultural variation by age. Future research could then test hypotheses with true random samples. If age-related technology literacy were shown to have an effect, then it would have significant policy implications for positive social change with the introduction of age-related technology literacy awareness in developmental education programs. Each of the areas under exploration in the research, therefore, provides potential insight into policy at MCC specifically and possible policy implications in the future derived from additional research.

Summary

The purpose of the study was to determine differences in completion rates among students who took teacher DMC and technology DMC when using the predictor variables of age, gender, and ethnicity; prior research on developmental education and completion rates will be discussed in the next chapter to establish a foundation for Tinto's theoretical framework.

Chapter 2: Literature Review

The problem at MCC is that over three-quarters of the students entering the college annually were directed to take a developmental education course in mathematics based on their placement test scores, yet half or less annually manage to complete the course. The purpose of this quantitative study was to compare completion rates of over 2,900 MCC students in teacher DMC and technology DNC when using the predictor variables of age, gender, and ethnicity.

The majority of Chapter 2 provides an overview of current literature in the study of developmental education. This begins with the history of developmental education in the United States. Contrary to popular belief, developmental education is not a new field and the problem of under-prepared students in not a new problem. Developmental education in the United States dates back to the 1600s, the beginning of higher education in the United States.

After a history of development education in the United States, the literature review is focused on the attributes of the developmental learner and examines student demographics including age, gender, and ethnicity and other factors that contribute to the likelihood that students will enroll in or be placed into developmental education courses. An abundance of literature exists discussing the failures of developmental education programs and the students served by these programs, so the literature review is then turned to an examination of student persistence when enrolled in developmental education courses. Following the examination of student persistence, the literature review includes a summary of promising models that are being used to increase developmental education success (Wladis, Offenholley, & George, 2014). For example, current literature on developmental education is focused on the failures of developmental education in general. As seen throughout the literature, the success rate of students who are placed in developmental education is low. Over the past few years several reforms have been tested. Some of the reforms discussed in Chapter 2 include acceleration (compression, fast track, modularization), support (tutoring, skill building, coursework, advising), and curriculum (revision, contextualization). The literature review concludes with an overview of several successful developmental education programs that have been redesigned.

Literature Search Strategy

The literature search for this study included Google Internet searches and database searches such as EBSCO, Gale Group, and First Search. In some cases, articles were located in conference websites. Key search terms included *developmental education, developmental education mathematics, remedial education, remedial education mathematics, developmental education demographics, history of developmental education, history of remedial education, minorities and developmental education, developmental education methodologies,* and *developmental education delivery*. With few exceptions (primarily theoretical foundations) the search for articles was limited to the last 5 years and included scholarly and peer reviewed articles, books and anthologies.

Theoretical Foundation

There are many theoretical perspectives covering multiple disciplines that can be applied to developmental education including those from adult education, disabilities studies, learning theories, multicultural education, student development theory, and vocational education (Collins & Bruch, 2000). Lundell and Higbee (2001) reviewed 23 disciplines and theoretical frameworks that apply to the field of developmental education, including adult education and student development theories, and pointed out there is too much variety in range and perspective of developmental education to adopt one theoretical model. They argued that a one-size-fits-all model does not work in developmental education yet much of the literature of developmental education has lacked a theoretical base (Lundell & Higbee, 2001). This assertion is supported by Chung (2001), who wrote that developmental education has been urged to embrace theories or "face academic extinction" (p. 19). However, there is no shortage of competing perspectives for solutions to address problems in development education.

One of the theories that researchers can use to examine developmental education is the theory of validation. This theory describes that when students receive validation from academic advisors, faculty, and other college representatives, these students acquire confidence (Acevado-Gil et al., 2014). Theory of validation is a foundational framework that is used to examine the validation experiences of students. Validation is an act that supports or enables a student and helps that student to feel capable of being successful and of learning both academically and interpersonally. That confidence then leads to better performance in the classroom.

A second developmental theory proposed by Kinney (2001a, 2001b), the functionalist theory, is focused on three concepts: self-regulation, demandingness, and responsiveness. Self-regulation can be defined as those feelings and beliefs directed toward reaching one's goals. Based on this theory, students who are self-regulating will be able to identify their skills' gap and look for ways to improve. They will seek out feedback and closely monitor their own progress. These students will take responsibility for their own learning. Kinney argued that self-regulation grows out of an academic environment that is both demanding (in expectation and excellence) and responsive.

Selectionism is also a theory that is commonly applied to developmental studies. Brothen and Wambach (2000) asserted that selectionism, "the idea that useful qualities are selected by environments" (p. 151), provides a philosophical framework for developmental education. Traditional developmental theory, according to Brothen and Wambach, has been focused on student deficits and impacts the way educators see developmental learners. In the case of the selectionist approach to developmental education, students are seen more as products of the environment in which they live and study. Knowing that, educators must create new learning environments. Although an array of theories offer microlevel insight into issues within developmental education, all of these perspectives can be seen as variations on a more holistic model developed by Tinto (1975).

Based on the significance of Tinto's (1975) model in relation to other theories in developmental education, the theoretical framework for this quasi-experimental quantitative study was Tinto's model of student retention. This theory addresses the level of student integration in regard to the completion rate of the student. Tinto's core argument is that students' completion rates are predicted by their academic integration at the college level. Academic integration, under the model of student retention theory, is defined as how a student perceives what is being learned and can relate to academic standards, or whether students can internalize a successful student identity. Tinto's model of student retention supports the idea of using the technology DMC to provide more integration among the students enrolled in these courses (Davidson & Wilson, 2013). Student integration, in this vein of theoretical development, is based most strongly on early student success, which creates a reinforcing sense of self as a successful student who belongs in the academic milieu.

Literature Review Related to Key Concepts and Variables

Developmental Education History

Boylan and White (2014) posited that the United States has offered some sort of developmental education since the beginnings of the nation's history. Harvard, founded in 1636, provided tutoring to those applicants who lacked the knowledge of Greek and Latin before they could be admitted. In 1795, when the University of North Carolina was founded, many students came underprepared for college-level work and were taught basic grammar, writing and arithmetic in the University's preparatory school before being fully admitted. In 1869, Harvard College president Charles William Eliot famously stated, "the American college is obliged to supplement the American school [. . .] [, so] [w]hatever elementary instruction the schools fail to give, the college must supply" (Brier, 2014, p. 11).

Arendale and Bonham (2014) divided the historical approaches to providing developmental education into six phases (see Table 1). During Phase 1, the1600s to the 1820s, developmental education was primarily limited to tutoring and available only to white, wealthy male students. From the 1830s until the 1869s, or Phase 2, academic preparation academies began to emerge across the country. These academies provided support to help prepare students for university-level courses in reading, writing, and mathematics. Again, most of those enrolled in the academies were affluent, White males. Because of this, according to Arendale and Bonham, a negative stigma was not attached to the developmental learning process. In 1849, 290 of the 331 students admitted at the University of Wisconsin were enrolled in one or more developmental courses. The Wisconsin Board of Regents of the University of Wisconsin acknowledged that the University, similar to other colleges in the United States, needed to create preparatory courses to prepare students for college-level work (White, Martirosyan, & Wanjohi, 2014, p. 21). During Phase 3 in the 1870s to the mid-1940s, the first Morrill Act (1862) brought about land-grant colleges, which increased access to women, minorities, and students of lower socioeconomic status (Arendale & Bonham, 2014). The need for developmental education expanded as students were required to study and improve their skills as a condition of enrollment. In 1879, 50% of Harvard's applicants were conditionally accepted because of low college entrance examination scores.

Since the early 1900s, community colleges have been recognizing the need for developmental education programs to provide assistance to students who enter college not ready to take developmental mathematics courses (Stewart, Lim, & Kim, 2015). In the period between the mid-1940s and the 1970s, the nation began to experience a shift. Previously, remediation was common for most college students, no matter their socioeconomic background (Arendale & Bonham, 2014). During Phase 4, however, students from affluent backgrounds were better prepared for college-level work than were their counterparts from disadvantaged and first-generation backgrounds. As a result, a negative stigma, still seen today, was attached to those students who enrolled in developmental education courses (Arendale & Bonham, 2014).

During Phase 5, the 1970s to the mid-1990s, the term developmental education began to be used in relation to all the services described previously. The idea behind the terminology was that all students had the ability to develop, grow, and learn as a result of additional assistance. Phase 6, the period between the mid-1990s and the present, has been a period during which much criticism has developed regarding the cost and the effectiveness of developmental education (Arendale & Bonham, 2014). One of the primary reasons for providing developmental education courses is the belief that all students should be given the opportunity to achieve a college degree (Brothen & Wambach, 2014).

Table 1

Six Phases of Learning Assistance History

Time Phase	Name(s) Commonly Used with Activities	People Served Predominantly During This Time Period
1600s to 1820s	Tutoring	Privileged white male students
1830s to 1860s	Precollegiate preparatory academy and tutoring	Privileged white male students
1870s to Mid-1940s	Developmental education classes in college preparatory programs and tutoring	Mostly white male students
Mid-1940s to 1970s	Compensatory education, counseling center, opportunity program, reading clinic, developmental education classes integrated in the institution, tutoring	Traditional white male students, nontraditional males and females such as war veterans, and federal legislative priority groups: first-generation college students, economically disadvantaged students, and students of color
Early 1970s to mid-1990s	Access program, developmental education, learning assistance, opportunity program, tutoring	Groups listed above, with an increase in older students who return to education or attend postsecondary education for the first time, and some general students who want to deepen mastery of academic content
Mid-1990s to the Present	Access program, developmental education, learning assistance, learning/teaching center, learning enrichment, opportunity program	Groups listed above, with an increase in general students, students with disabilities, and faculty mems who seek professional development in learning and teaching skills

Note. Information from Arendale and Bonham (2014).

Beyond the research summarized to this point, developmental education has been a debated issue in academia (Boylan & Trawick, 2015). Scholars tend to agree that students entering developmental education are either underprepared or returning to college after a delay that has affected their academic proficiency (Asmussen & Horn, 2014). However, the struggles of developmental education in providing a successful, seamless pathway to further postsecondary education or a career have been fairly consistent along its historical trajectory (Brier, 2014).

Developmental Student Demographics

High school students who come into college have a belief that they are ready for college-level courses (Smith, 2016). In fact, 86% of students believe they will not be placed into developmental education courses, however 67% of students entering into college are placed in developmental education courses. Armington (2003), discussed five categories of developmental mathematics students. The first category is that of students who have the mathematics ability or aptitude, but either the students lack the motivation to complete the course or they are completely disinterested in the course. As a result, these students have fallen behind in mathematics. The next category is defined by those students who have the skills needed to learn and also possess the motivation to learn but lack the required math skills. The third category of learner, while motivated to learn, lacks both the learning skills and the mathematics skills to produce college-level work. The fourth category is made up of those students who have a documented learning disability. Finally, the fifth category is made up of students who lack learning skills, mathematics skills, and motivation.

Some students in developmental education face obstacles that have only over the last few decades become a focus for adequate accommodation in terms of disabilities (Mamiseisghvili & Koch, 2012). However, research in placement has shown that a range of factors influence student placement into developmental education mathematics (Benken, Ramirez, Li, & Wetendorf, 2015; Couturier & Cullinane, 2015; Hudesman, Millet, Niezgoda, Han, & Flugman, 2013; Leon & Alexander, 2014; Silva & White, 2013). A range of factors not only affects placement but also affects persistence (Davidson & Petrosko, 2015; Rendon & Munoz, 2011; Scrivener & Weiss, 2013). One of the most common issues affecting both placement and persistence is academic literacy or a kind of acculturation to academic expectations (Armstrong, Stahl, & Kantner, 2015; Cummings, 2015; Guy, Cornick, Holt, & Russell, 2015). The research on academic literacy strongly intersects with Tinto's theoretical framework in the importance of student identity within the academic milieu. Some of the most common demographic factors follow.

Age. There is a significant gap in completion of developmental and traditional mathematics courses, or teacher DMC as defined in this study, among ethnicity and age groups (see Stewart et al., 2015). According to researcher Dasinger (2013), age is a strong indicator of whether students will complete their course. Research has shown that younger students are more likely to complete course work and graduate than older college students (Dasinger, 2013). A report released by the National Center for Education Statistics indicated that enrollment of nontraditional students was increased by 19% during the years of 2006 and 2007. Nontraditional students are defined as: (a) students who do not enroll in college courses the same year as they graduate high school; (b) students who are not enrolled in college as a full-time student; (c) students who work more than 35 hours per week; (d) students who are financially independent and able to claim independent status on their financial aid; (e) students who have dependents (not including a spouse); (f) students who are single parents; or (g) students with a GED instead of a high school diploma (Dasinger, 2013). If nontraditional student populations are on the rise in college, and they are also less likely to complete a course, it stands to reason there will be an increased need for developmental education in the future.

For the purpose of this study, nontraditional students will be primarily identified by age. Using age both emphasizes the common definition proposed by the National Center for Education Statistics (NCES) and reinforces the rationale for including age in the research design. According to the NCES (2017), nontraditional students often have multiple qualifiers distinguishing them from traditional students, such as part-time student enrollment, full-time employment, age of 25 or greater, and/or family responsibilities with spouses and/or children. However, the presence of only one of the possible variables for identification as nontraditional represents a minimal level of nontraditional status while more variables indicate stronger nontraditional status (NCES, 2017). Therefore, age tends to be one of the most reliable determinants of nontraditional status because students age 25 or greater have a much high likelihood of multiple variable indicators of nontraditional status (NCES, 2017). Thus, age in this study helps to capture nontraditional student status in those age 25 or greater.

Research has shown that delaying college enrollment has strong correlation with placement into developmental education as well as perhaps generating other issues in persistence due to structural issues in daily life (Fike & Fike, 2012). Again, related to Tinto, if students cannot prioritize the student identity due to competing identity pressures or a sense of inability to succeed, then success can indeed be out of reach by a kind of self-selection for failure. Although some colleges have worked to improve structural support programs for all students, which can mediate some effects of age, it may still be a powerful factor in student outcomes (Bettinger, Boatman, & Long, 2013; Hodara, 2015). The data provide an opportunity to explore the way, if any, that the course design structure could affect course completion rates based on age. The same kinds of observations could be made in terms of gender and ethnicity, each alone in multiple regressions and then in combinations to tease out any possible interaction effects or relational effects.

Minority students. Colleges are showing a lower enrollment rate among minorities for traditional mathematics courses, or teacher DMC as defined in this study (Stewart, et al., 2015). Researchers Atuahene and Russell (2016) stated that minority students are less likely to come to college prepared to take college-level courses. Forty percent of white students come to college prepared to take college-level courses as compared to only 23% of African American students and 20% of Hispanic students (Atuahene & Russell, 2016). Furthermore, 82% of the workforce in mathematics, science and engineering are white. This compares to 10.4% Asian American, 3.4% African American, and 3.1% Hispanic populations in the same areas of the workforce (Atuahene

& Russell, 2016). The study also indicated that 95% of white students are placed in college-level mathematics course while only 39.6% of African American students are placed in the comparable college-level mathematics courses. Therefore, it can be determined that white students are taking part in more rigorous mathematics programs (Atuahene & Russell, 2016). The state of Texas shows overwhelming percentages of nonwhite students in developmental education as well.

According to Complete College America 2013, 72% of African American students and 57% of Hispanic students were placed in developmental courses in the state's community colleges (Saxon & Morante, 2014). Table 2 presents demographic data of undergraduate students enrolled in developmental education courses.

Table 2

Percent of Freshmen Taking Developmental Courses

Student Characteristics	1999-2000	2003-04	2007-08
Total	28.8%	22.1	23.3
Sex and race/ethnicity			
White	24.3	19.7	19.9
Black	37.3	27.4	30.2
Hispanic	37.8	26.8	29.0
Asian/Pacific Islander	34.9	20.1	22.5
Other or Two or more races	32	22	21.8
Male	28.5	20.7	21.6
White	24.7	19.0	18.7
Black	38.3	24.9	28.7
Hispanic	34.8	24.4	28.3
Asian/Pacific Islander	35.3	21.0	20.8
Other or Two or more races	32.0	22.0	21.8
Female	29.8	23.1	24.7
White	23.7	20.3	21.0
Black	37.7	29.0	31.2
Hispanic	42.5	28.6	29.5
Asian/Pacific Islander	35.6	19.3	24.2
Other or Two or more races	32.9	25.4	32.2
Age			
18 or younger	24.4	23.1	23.7
19-23	31.9	22.6	23.8
24-29	34.7	20.1	22.0
30-39	29.5	17.5	20.3
40 or older	24.9	20.6	18.4

Note. Information from Hargens (2013).

It is worth mentioning that despite research that has provided strategies to address the gender gap in math, education pathways and careers in science, technology, engineering, and mathematics (STEM) still remain disproportionately male (Hacker, 2016; Leyva, 2017). Some program reforms and innovations in regions of the United States South suggest that the ethnicity and gender gap may be related to stereotype threat, per the research orientation of exploratory nature in this study, but the research has not been conclusive (Clotfelter, Ladd, Muschkin, & Vigdor, 2014; Cullinane & Treisman, 2010; Zachry & Diamond, 2015; Smith, 2015; Sivley, 2013). Therefore, both placement and persistence are complicated issues needing careful scrutiny to understand better.

Developmental Education Persistence

Many arguments have been made that developmental education does not boost completion rates in 2-year colleges and 2-year universities. Research from the Exxon sponsored National study of Developmental Education concluded that students who take fewer developmental education courses are more likely to complete college. The Little Hoover Commission 2000, also determined that students who are enrolled in developmental courses have a low likelihood of completing their degree (Brothen & Wambach, 2014). Scott-Clayton, Crosta, and Belfield (2012) maintained that fewer one of the primary reasons students do not complete college is that they lack basic skills and are enrolled in developmental courses. Less than 25% of college students who are taking developmental education courses are likely to complete within 8 years. In comparison, more than 40% of students who take college-level education courses are likely to graduate within the 8-year time period.

Authors Stewart, et al. (2015), maintained that students who were not enrolled in developmental education courses, but rather enrolled in college-level courses were more likely to complete the degrees and graduate from college. Carfarella (2016b) wrote that college students who do not successfully complete their first developmental course are likely to drop out of college within a year. Therefore, and consistent with the use of Tinto's retention theory, early success academically is crucial to allow students the opportunity to become socially integrated, and thus more fully integrated, into the institutional or postsecondary culture overall. The importance of early success can be seen in the large numbers of students who begin their college careers in developmental education. Around two-thirds of incoming college students are placed in developmental education courses (Jaggars, Hodara, Cho, & Xu, 2015). Students who are placed in the developmental mathematics sequence must take an average of three developmental mathematics courses before being placed in college-level mathematics courses, all of which strongly reinforces the need to evaluate the most effective course content delivery methods to promote early student success.

As an example of the struggles of students to manage academic integration, only 28% of students in community colleges were able to successfully complete their course work within a 6-year period (Li et al., 2013). Although placing students in developmental mathematics courses increases the knowledge of foundational skills, it also increases the chances of attrition rates among these students (Li et al., 2013). Methvin and Markham (2015) maintained as few as 8% of students in developmental programs earn a degree. The authors claim that only 6% of students who begin in developmental mathematics courses complete the math sequence in 1 year and only 15% of those students complete the math sequence in 2 years. Students who do complete the developmental education course have only a 22% chance at two-year colleges and 32% chance at four-year colleges of successfully completing their first college level course, in their program of study, in the first two years (Fulton et al., 2014). Furthermore, only 9.5% of developmental education students will graduate from their two-year college within three years (Fulton et al., 2014). The outcome of placing students in developmental mathematics courses is costing colleges and students financially and impacting college completion rates (Ariovich & Walker, 2014). Thus, the most efficient delivery of course content to promote student success has benefits not only for students in attainment, or lack thereof, of their college and career aspirations but also has financial benefits for all stakeholders in education.

Factors Contributing to Low Success Rates in Developmental Education

In 2003 the US Department of Education determined that two to three billion dollars a year was spent on developmental education courses. Recent estimations (Scott-Clayton, et al., 2012) are has high as seven billion dollars a year. Bailey, Jaggars, and Jenkins (2015) maintained costs to the average community college student increased by 89% in tuition and fees alone when enrolled in developmental education courses before college-level courses. Even with this amount of money being spent, historically, there is little to no evidence that developmental education has been a successful avenue for colleges (Moss, Yeaton, & Lloyd, 2014).

Research studies have shown that developmental education courses have not been successful in increasing completion rates, and furthermore have often hindered students from being successful in college-level courses in the future (Landers & Reinholz, 2015). Landers and Reinholz (2015) cited a study of over 250,00 students from 57 community colleges in which only 33% of students placed into developmental mathematics courses were able to complete the developmental coursework and their college level mathematics class within 3 years. When students were placed into a developmental mathematics sequence of three or more courses, only 17% completed those courses. For many years community colleges have struggled with addressing deficiencies in academics among college students. According to Stewart et al, (2015), community colleges have a long history of placing students in developmental education programs that many believe are teaching skills that should have been mastered before entering college.

There are three major factors that contribute to the failure of developmental education programs according to Jaggars, Hodara, Cho, and Xu (2015). Those factors include: outside forces, placing students in the wrong developmental education courses, and lack of motivating curriculum. Others (Edgecombe, 2011; Hodara, Jaggars, & Karp, 2012) hypothesized that the three main factors that affect completion rate among students in developmental course are: placement errors, de-motivating curricula or pedagogy, and the power of external pulls. Cafarella (2014) added student apathy, homework habits, and work schedules to the list. This section of the literature review will cover each of the above-mentioned factors that may contribute to a developmental learner's failure. The factors are discussed as they are broadly categorized in the literature: external forces, placement errors, and relevant curriculum.

External factors. According to Saxon and Morante (2014), one of the external factors that influences the completion rate of students enrolled in developmental courses is that the placement tests do not measure the drive, motivation, or desire of a student. These externals factors could have an impact on successful completion rates among college students who are in developmental mathematics programs. External factors such as age, motivation, and personal goals impact student grades by 41 % and therefore, according to the authors, should be included in the assessments for placement in developmental courses. Cafarella (2014) argued that apathy and low attendance are both reasons for high rates of noncompletion in developmental education. Students lack the motivation and fall into patterns of skipping class, failing assignments, and dropping out.

There are other factors that impact completion rate among college students. Many students can experience unforeseen circumstances such as job loss, family emergencies, financial issues, and child care issues. These factors also impact completion rate among students in both developmental and college-level mathematics courses (Jaggars et al., 2015). Going to both work and class becomes a delicate balancing act for many working students. Sixty percent of community college students who left college before graduation stated they had to work full time to support their families (Cafarella, 2014).

Placement tests. Acevedo-Gil et al. (2014) pointed out that standardized placement tests, although commonly used to measure college readiness and to place students in the appropriate preparatory coursework, are not an accurate measure of college readiness. The authors argue that following their assessment into developmental education nearly two-thirds of students do not bother to enroll and that the very act of assessing into developmental education lowers students' academic confidence.

Placement tests have a margin of error that many times puts students in the wrong level of developmental mathematics courses. Many students are placed in developmental education courses that are either too high or too low according to their abilities instead of their placement score. Research shows that students who are misplaced into a lower level course are less likely to complete due to the course being too easy, or the student not seeing the value (Jaggars et al., 2015). According to the Community College Research Center (2017), a substantial number of students whose placement scores indicated the need for remediation yet chose to bypass the developmental courses and move directly into college-level courses were nonetheless successful in those courses.

Colleges use a variety of measures to place students in developmental mathematics courses. Some community colleges use a placement test that is given before the students are enrolled in classes. According to Saxon and Morante (2014), many colleges are giving placement tests without providing students with study guides, opportunities to study, or even the knowledge that they will have to take a placement test in order to get into college-level courses. Other colleges use high school GPA and examine courses taken in high school to determine college readiness. Using the high school GPA is often not the best indicator of success, especially for college students who have graduated more than 5 years ago. Furthermore, many colleges are only using one form of measurement to place students instead of using a variety of information on the student to effectively place the student in developmental or college-level coursework (Saxon & Morante, 2014). According to Jaggars et al. (2015), many of the assessments that are being used in college have a measurement error, therefore many students who are being placed in the developmental courses could have started their college careers in college-level courses and completed with academic success.

Relevance of curriculum. Developmental courses many times include teaching of subskills without tying the skills back to college level course work (Jaggars et al., 2015). Many students see these subskills as meaningless in isolation and not connected to the college-level work that will prepare them for their career. Developmental courses are often seen as not challenging students enough to keep them interested in the course work. Colleges have begun looking at accelerated developmental mathematics courses that allow students to progress quickly through the developmental work and begin in the college-level mathematics courses earlier than they would have had the students been caught in the developmental sequence (Jaggars et al., 2015).

According to Wong (2013), the National Center for Academic Transformation offers six models to consider when addressing curriculum change in developmental education:

- The emporium model uses computer software along with mentoring and individualized assistance provided by tutors or instructors.
- The supplemental model supplements classroom instruction with out-of-class activities, including technological activities.

- The replacement models replace lectures with online activities.
- The fully online model replaces all classroom time with online activities and software.

Factors Contributing to Success in Developmental Education

Pruett and Absher (2015) studied nearly 24,000 developmental education students to determine what variables impacted retention in developmental education classes. The researchers concluded the following:

- Students engaged in educational activities during their first year were retained at a 24.7% higher rate than those students who were not engaged in educational activities.
- Students who spent 6-10 hours preparing for their developmental education courses were retained at a rate of 8.8% higher than those students who spent just 1-5 hours preparing for class.
- Students who spent time participating in college-sponsored student activities were retained in developmental courses at a rate 18.1% higher than those students who did not participate in college-sponsored student activities.
- Students whose parents held at least an associate's degree were retained at a rate of 11.4% higher than those students whose parents had no college degree (Pruett & Absher, 2015).

Promising developmental math models. Community colleges have begun looking at ways to increase completion among students who are enrolled in developmental mathematics courses. Many colleges are looking into research-based teaching strategies to try to improve the successful completion rate of student who are enrolled in developmental courses. Some community colleges are looking at eliminating developmental education courses completely (Saxon & Morante, 2014). Perhaps one of the more successful ways colleges are helping students to complete their developmental education courses is through accelerated methods. The following pages detail methods through which students have had some success by using acceleration.

Accelerated models. Many colleges have put accelerated programs into place to address outside factors that influence completion of the developmental education sequence. Accelerated programs are designed to move students through developmental mathematics courses by combining them into a single course. Students may then finish at a quicker pace, be retained, and complete the courses (Jaggars et al., 2015). Accelerated models are programs in which colleges provide instruction in a shortened time period. Accelerated classes meet more often than the standard teacher DMC. Accelerated programs can be beneficial to students who were placed in developmental education courses because they oftentimes pair college level curriculum with developmental education curriculum (Jaggars, Hodara, Cho, & Xu, 2015). Most accelerated programs, according to Fong and Visher (2013), fall into the following four categories:

- Developmental education courses are given in a compressed time frame. Although the total number of class hours may be the same as in a standard sixteen-week course, in a compressed course, students may meet for only eight weeks. Using this format, students can move swiftly through their developmental education sequence (Fong & Visher, 2013). Edgecombe

(2014) states that compressed courses are one of the most popular strategies used to improve outcomes of students in developmental education. Edgecombe (2014) compared success rates of students who participated in compressed courses in 5- to 9-week formats with those who took standard 16-week courses. The results found that students completed the compressed courses at a higher rate than those taking standard 16-week courses (Edgecombe, 2014).

- Developmental education courses are divided into modules, each module focusing on one skill set. Students are then able to complete only the modules they need, work at their own pace, and complete multiple levels in the developmental sequence in one semester. At a community college in Cleveland Tennessee, students have been placed in accelerated programs where the developmental skills are separated into modules. Students then work on the modules as homework. They can also take quizzes and tests within the modules. Students placed in accelerated models can also finish the course in less than the standard semester (Cafarella, 2016a).
- Developmental education curriculum is also being redesigned with the intent of decreasing the number of courses students must take. For example, students who major in certain areas will focus on a redesigned course that aligns with that area.
- Developmental education courses are being mainstreamed and paired with nondevelopmental courses. Using this model, students are enrolled in regular

college-level courses and receive levels of support such as tutoring or study courses. The advantage of this model, as with the previous models, is that students are able to condense the amount of time they take to complete their developmental studies and move into college-level courses (Fong & Visher, 2013). Many times, the accelerated programs are paired alongside developmental education courses so that students can take classes towards their degree and the developmental courses at the same time (Fulton et al., 2014). Developmental courses are taught immediately following the college level course.

Modularized. Examples of successful modularized programs include Math My Way at Foothill Community College and the Smart Math program at Jackson State Community College. In both cases the math curriculum is broken down into a series of modules. Math My Way divides students into groups by skill level. Students meet with instructors for two hours a day, every day of the week to learn and master key concepts through games and drills. Jackson State's Smart Math program is broken into 12 online modules with assistance and structures in a math lab. Students are required to attend and work in the math lab at least three hours each week. Capable students pass quickly through the modules, demonstrate competency and move to the next module. Evaluations in both programs show that student gains in GPA and persistence in subsequent college-level courses. Foothills Math My Way learners earned a 20% higher pass rate in college-level math than did nonparticipants, and the Jackson State program showed similar results (Rutschow & Schneider, 2011). Another pair of successful modularized programs were developed in Virginia and South Carolina, with very similar modularized components (Bickerstaff, Fay, & Trimble, 2016). In general, then, a modularized curriculum appears to provide a structure in manageable pieces for students to consume comfortably academically. But a fast track approach also can be successful.

Fast track. According to Rutschow and Schneider (2011), fast track courses are courses offered in a condensed time frame. They are designed for developmental education students who are more advanced and generally complete a screening process which confirms the student has the ability to be successful in a condensed, rapidly moving pace. In order to participate in the Community College of Denver's Fast Start program for example, students must first meet with the counselor to ensure they have the proper understanding of the structure of the course. Fast track courses often require daily attendance and students may or may not enroll in a cohort. Fast track courses often use computer software to help facilitate self-paced learning. Fast track programs historically have had many successes. For example, courses at two Ivy Tech Community College students' course pass rates showed an increase, and fewer students withdrew from fast tracked courses as compared to students engaged in standard semester-long format developmental education courses. A study at Mountain Empire community college showed that fast track math students not only completed and passed the math course but also persisted at higher rates. Similarly, the University of Maryland College Park discovered that almost all the students in the fast track programs moved on to college level courses and performed comparably to students who went directly into the course (Rutschow & Schneider, 2011). Table 3 shows the results of accelerated methods including Fast Track courses, modularized courses, and mainstreamed courses (developmental and college-level courses).

Table 3

Summary of Acceleration Strategies

Program		Fast-Track Courses	Modularized Courses	Mainstreaming into College-level Courses
Rigorous Research				
	Findings			Positive outcomes: Higher rates of attempting and completing college- level English and subsequent courses
	Studies			(Jenkins et al. (2010)
Promising Trends				
	Findings	Positive outcomes: Increased progress through developmental education; increased course pass rates, grades, and rates of persistence	Positive outcomes: Higher pass rate in college-level courses; faster progress through developmental course sequence	Positive outcomes: Higher levels of persistence; comparable or higher pass rates in college-level course
	Studies	Brown and Ternes (2009); Zachry (2008); Adams (2003); Brancard, Baker, and Jensen (2006); Bragg (2009)	Bassett (2009); Bragg and Barnett (2009); Epper and Baker (2009)	Goen-Salter (2008); Adams, Gearhart, Miller, and Roberts (p.303 in this book); Jenkins (2009)

Note. Information from Rutschow and Schneider (2011).

As is evidenced in Table 3, accelerated methods such as fast track courses, modularized courses, and mainstreamed courses do provide higher pass rates and levels of persistence with college-level courses.

Research by Seldon and Durdella (2014) indicated that students enrolled in compressed or accelerated developmental math, English, or reading classes were more likely to be successful than those students enrolled in a standard 16-18-week course. However, those students enrolled in a compressed 8-9 week course were more successful than those students enrolled in a compressed 5-6 week course in both English and math. Table 4 shows the success rate breakdown by both in math, reading, and English by 5-6 week courses, 8-9 week courses, and 16-18 week courses. Table 5 shows success rates by course length, gender, ethnicity, age, and GPA.

Table 4

Success Rates by Course Length

Characteristics and Success	5-6 Week Course	8-9 Week Course	15-18 Week Course
English			
English 20	x^2=195.175*75.		
Percent successful	80	86.90	56.70
Math			
Math 20	x^2=23.804*		
Percent successful	57.91	49.37	48.38
Math 40	x^2=47.344*		
Percent successful		67.08	53.56
Reading			
Reading 42	x^2=15.072**		
Percent successful	80.62		63.11
Reading 43	x^2=21.165*		
Percent successful	75.00		63.53
Reading 54	x^2=17.557*		
Percent successful	81.19		66.82

Note. The total number of students in English 20 is 4,636; in Math 20, 5,410; in Math 40, 6,000; in Reading 42, 926; in Reading 43, 2,904; and in Reading 54, 1,285.
*$\alpha \leq .000$.
**$\alpha \leq .001$.
(Seldon & Durdella, 2014).

Table 5

Success Rates by Course Length and Social and Academic Characteristics

Characteristics and Success	5-6 Week Course	8-9 Week Course	15-18 Week Course
Gender	x^2=1.348*		
Male	69.13	69.19	51.92
Female	71.98	74.12	57.34
Ethnicity	x^2=214.667**		
Asian/Pacific Islander	77.78	87.75	62.20
African American	53.78	58.91	42.78
Latino	71.28	70.52	55.79
White	62.79	78.18	61.12
Other	72.22	69.96	55.70
Age	x^2=10.785***		
Below 25	66.29	71.57	52.78
25 and over	78.82	74.29	62.80
GPA	x^2=77.554**		
Below 2.0	54.45	122.51	38.09
2.0 and over	76.91	77.42	63.28

Note. The total number of students is 21,165 for gender, ethnicity, age, and GPA.
*a = .510.
**$a \leq .000$.
***$a \leq .005$.
(Seldon & Durdella, 2014).

As seen in Table 5 students enrolled in 8-9 week courses are more successful than students in 16-18 week courses regardless of age, gender, ethnicity, and GPA. Students enrolled in 5-6 week courses are more successful than those enrolled in standard 16-18 week courses; however, they are not as successful as those enrolled in 8-9 week courses. The exception is those students enrolled in 5-6 week courses who are age 25 and over who were more successful in 5-6 week developmental education courses than were those enrolled in either 8-9 week courses or 16-18 week courses. According to a study cited by

Cafarella (2014), models that provide students with individual tutoring accelerate the completion of the developmental education series so that students are able to finish more than one developmental course in one semester. Other successful educational reforms include learning communities, contextualized courses, and learning supports. Each of these will be explored in detail in the following pages.

In the aggregate, then, there may be student-specific benefits across all of these successful programs, and perhaps a more individualized approach, either online or in the classroom may be effective. Online learning shows promise for students at their own pace (Lenzen, 2013). A wide array of studies into teaching innovation also generally finds teacher innovation to be most effective when specific student needs are addressed through varied teaching methods, activities, and approaches (Braco, Austin, Bugler, & Finkelstein, 2015; Bickerstaff, Lontz, Cormier, & Xu, 2014; Hodara, 2011a, Hodara, 2011b; Walker, 2015). The recommendations for improving pedagogical approaches mirrors many aspects of broad education structural reform suggested by researchers and leaders in education (Brothen & Wambach, 2004; Crisp & Delgado, 2014; Kincaid, 2013; Lass, 2014; Merisotis & Phipps, 2014; Sowers & Yamada, 2015). However, it can be useful to look at peer-learning strategies as well.

Learning communities. Learning communities are groups of students who are working together to complete one or more course during a semester. Learning communities are one strategy that some community colleges have implemented in hopes of increasing the successful outcomes of developmental courses. A study of 6,974 students from six colleges who tested into developmental mathematics were placed into learning communities. The research concluded that unless the learning communities are highly structured and include interventions, they are not likely to make a significant impact on completion rate or graduation rate (Weiss, Visher, & Wathington, 2015).

Learning communities are popular for developmental education students at community colleges (Rutschow & Schneider, 2011). These communities often include a cohort of learners who take both a developmental education course and a college-level credit course. Oftentimes these communities also include a student success course which focuses on the development of study skills. The results of learning communities have been positive, although modest. Over a dozen institutions were surveyed and found a significant relationship between the students' participation in the community and their level of engagement. Students in learning communities form bonds with their fellow students and with their faculty, and they tend to persist in college during the following year at significantly higher rates than so those students in comparison groups who did not participate in a learning community. Although the results for learning communities are impressive when considering engagement and persistence, the findings do not generally suggest that the programs lead to higher academic outcomes, according to authors Rutschow and Schneider (2011).

Contextualized learning. Rutschow and Schneider (2011) maintained that best practices in developmental education often include contextualized instruction. This type of instruction generally focuses on the basic skills of reading, writing, and math and those subjects are taught in conjunction with other course content. For example, a student in a vocational field may be taught mathematics as it relates to automotive technology or welding or nursing. Contextualized learning offers opportunities to integrate developmental skills into mainstreamed curriculum. One well-known contextualized learning model comes from Washington State's integrated basic education and skills training or I-best Program. In this model adult basic education instructors and English as a second language instructor's work together with vocational faculty to teach in vocational programs. Another promising program is the Charles Stewart Mott Foundations Breaking Through Initiative that has been used in numerous colleges throughout the country with positive outcomes including an increased rate of college readiness improvements in progress toward completing students occupational certificates (Rutschow & Schneider, 2011). Table 6 shows an overview of the positive outcomes in contextualized programs including I-Best and learning communities.

Table 6

Vocational Programs

Program		I-BEST	Breakthrough	Learning Communities
Rigorous Research				
	Findings	Positive outcomes: Increased progress Into credit-bearing courses; higher persistence rates; earned more credits that counted toward a credential; higher rate of earning occupational certificates; learning gains on basic skills tests		Modestly positive outcomes: Impacts on student engagement, credits earned, and progression through developmental course sequence; positive effects
	Studies	Jenkins, Zeidenberg, and Kienzl (p. 294 in this book).		Scrivener et al. (2008); Weiss, Visher, and Wathington (2010) Weissman et al. (2011); Visher, Schneider, Wathington, and Collado (2010)
Promising Trends				
	Findings	Positive outcomes: Increases in college credits earned; improvements in access and completion of workforce training; some gains in English language skills	Positive outcomes: Increased rates of college readiness; improvements in progress towards completing occupational certificates	Positive outcomes: Increased student engagement and persistence
	Studies	Washington State Board for Community and Technical Colleges (2005)	Bragg and Barnett (2009)	Engstrom and Tinto (2008); Tinto (1997) Zhao and Kuh (2004)

Note. Information from Rutschow and Schneider (2011).

Learning supports. Rutschow and Schneider (2011) stated that academic supports often seen in developmental education programs include tutoring, both group and individualized, labs, computer software, supplemental instruction, and mentoring. Good advising, both academic and career, are often included in development education. Support workshops and study skills can also be seen as academic support. Table 6 provides an overview of the positive outcomes and promising trends in the areas of student support for developmental education learners (Rutschow & Schneider, 2011).

Peer tutoring, orientation courses, and study skills courses have a positive impact on developmental learners pass rates, transfer rates, and overall GPA. Those learners involved in supplemental instruction showed higher grades and persistence rates. Those learners who were enrolled in developmental education courses and involved in enhanced advising also showed increases in persistence, yet at a lower rate than those who participated in tutoring, orientation courses, or supplemental instruction (Rutschow & Schneider, 2011).

Self-paced learning. Self-paced learning modules are being implemented in colleges in an effort to increase successful completion of developmental mathematics classes. Institutions are using self-paced computer modules where students are given the opportunity to work in their skill deficit areas. Some examples of the self-paced learning programs are: Pearson's MyMathLab, Enable Math, and ALEKS. The self-paced modules provide lecture, pretests, post-tests, tutorials, and homework. Some of the self-paced learning programs are tailored to the specific math skills a student needs to complete successfully their program of study. Students who have been given the opportunity to learn specific skills related to their program of study have shown an increase in completion rates (Ariovich & Walker, 2014).

One of the most popular forms of self-paced learning takes place in a computer lab where there is an instructor available to answer questions. This is named the "emporium model" and was established by Virginia Tech University. Instructors that use the "emporium model" minimize the amount of teaching and rather focus on working with individual students on their individual skill deficits (Fulton et al., 2014).

Ariovich and Walker (2014), concluded that the majority of students who are enrolled in self-paced learning programs feel that they would benefit more if they had the help of an instructor to assist them through the mathematical problems rather than a tutorial on a computer. Many students believed they were teaching themselves how to complete math problems. Students who are successful in self-paced modules tend to be self-motivated, goal orientated and able to work in a free learning environment (Fulton et al., 2014).

Computer-aided math software. Many colleges are beginning to incorporate the use of computer software into their developmental mathematics courses. Wladis et al. (2014), determined that colleges are showing some success in using computer-aided software in their developmental programs, however, the research showed that the computer software alone was not enough and the programs needed to be enhanced and could not only rely on the software itself as a means for successful completion of the course. Zientek, Skidmore, Saxon, and Edmonson (2015) cited researchers (Gavitt, 2010, Spradlin, 2009, & Taylor 2008), who concluded that students in three studies did not show more significant improvement in developmental courses when they were able to use computer software (Zientek et al., 2015).

Developmental Mathematics Case Studies

Several institutions have developed programs in mathematics to help the under-prepared learner be successful not only in completing developmental mathematics courses, but also in completing higher level mathematics courses. The key components of those programs are highlighted in the following pages.

Fong and Visher (2013), in their Achieving the Dream Study, focused on two accelerated math programs: Math Redesign at Broward College and ModMath at Tarrant County College. Math Redesign compressed a 16-week course into an 8-week course. The accelerated method of the course allowed students to complete two levels of math in one semester. Students attended class 4 days a week and completed the same number of class hours as they would have in a standard 16-week course. Through this intense model, students were thought to engage more and improve their learning. Students gained momentum as they progress through a shortened period in developmental education (Fong & Visher, 2013).

Math Redesign also provided a format through which instructors were able to deliver immediate feedback. Instructors reviewed feedback and worked individually with students. The course also allowed for mini lectures and collaborative problem solving. Students engaged with one another and with the instructor to practice what they learned in the mini lecture. Another aspect of Math Redesign was the use of a web-based assessment and instruction program, ALEKS (Assessment and Learning in Knowledge

Spaces). Therefore, Math Redesign is very close to the redesign initiated by MCC, shifting from teacher DMC to technology DNC. Students used ALEKS outside of the classroom to master skills they struggled to learn. Students interviewed as part of the study reported spending up to 100 hours using ALEKS during the 8-week program. Figure 2 shows the results of the Math redesign course, or technology DNC, when compared to a teacher DMC over a 6-year period.

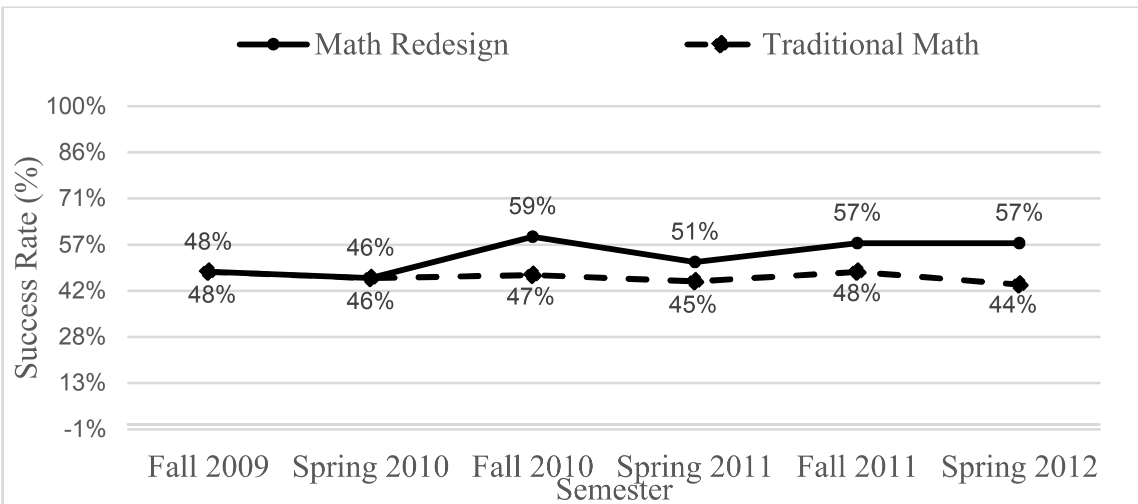

Figure 2. Math success rates in prealgebra, elementary algebra, and intermediate algebra. $N = 50$ (Fong & Visher, 2014).

Tarrant County College's ModMath used a series of nine modules developed from three levels of developmental mathematics courses. Each of the modules was used over a 5-week period. Students enrolled in three modules per semester, thus they were able to complete their course in the same amount of time it would have taken them to complete a standard 16-week course. However, if the student was motivated and understood the work, she or he could complete more than three modules during the semester as the program was self-paced and allowed students to stop in or stop out of the course depending on the issues in their lives. Students worked in a "one-room schoolhouse" environment where instructors and lab aides moved from student to student and level to level. ModMath used a Web-based instruction software, MyMathLab, in class, and students gained additional assistance from the instructor. Figure 3 displays the difference in scores of those students enrolled in ModMath and those students enrolled in standardized developmental mathematics courses without the individualized learner component of ModMath.

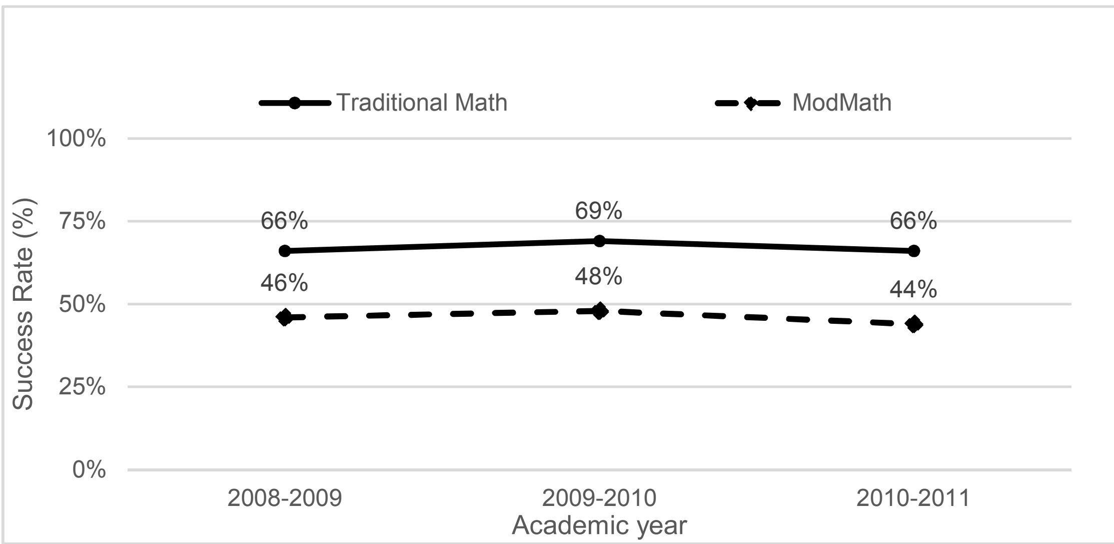

Figure 3. ModMath and traditional math success rates in developmental courses. From Fong and Visher (2014).

It is evident from this graph that those students enrolled in ModMath were more successful than those students enrolled in a standardized developmental mathematics course.

A report by Quint, Jaggars, Byndloss, and Magazinnik (2013) focused on 15 community colleges who were part of "The Developmental Education Initiative" funded by the Lumina Foundation. The report found that the 15 colleges, collectively, implemented 46 varied strategies categorized into the following four broad types: (a) policy strategies related to college-wide policies of placement, registration, and course sequencing, (b) instructional strategies that changed the content and/or modality of the courses, (c) support strategies which ranged from assistance in academics to social and personal issues, and (d) high school strategies which focused on assisting students before they reached the college level in an effort to increase the students' skills.

There were four strategy objectives that guided the 46 strategy types: The first strategy objective was acceleration. The purpose of acceleration strategies was to create opportunities for students to move quickly through developmental education courses and into college-level work. Acceleration strategies included computerization, individualization, modularization and compression. The second strategy objective was defined as avoidance strategy, which enabled students to avoid developmental education courses by better preparing for the placement test. The third strategy objective was that of support and included academic support, tutoring, personal counseling, supplemental instruction and advising. The final strategy objective was called instructional relevance and included changes to the curriculum or teaching modality. The following pages detail the strategies used by the 15 colleges who participated in the Developmental Education Initiative. In some cases, the colleges created new strategies. In many cases, the colleges scaled up existing strategies.

Coastal Bend College started four new strategies for developmental education students. The college enacted a policy that mandated continuous enrollment in the development education sequence. Students were required to begin with the lowest level of developmental education courses and work their way through the sequence to college-level courses. The second new strategy was to enact a support system in the form of case management. College staff were responsible for working with individual students. The third and fourth strategies were instructional. Coastal Bend College used a compression method of delivering developmental education by moving 16-week courses into 8-week courses, thereby allowing students to complete their developmental education sequence faster. The final instructional strategy developed by Coastal Bend College was to provide short and intensive fast track courses.

Cuyahoga Community College developed three new strategies as part of their developmental education initiative. The first strategy was in the area of support and provided for supplemental instruction in both English and math. Supplemental Instruction (SI) is a program which provides peer assisted learning opportunities. The second area of support was to provide mentoring for students in their math classes. In other words, students who were enrolled in college-level math courses were provided with a mentor and additional support to be successful in those courses. In all three cases with the Cuyahoga Community College initiatives used strategies that were scaled up from existing strategies.

Danville Community College instituted three new strategies as part of their developmental education initiative. First, an instructional strategy based on the objective of accelerating students' progress through the developmental education sequence. The strategy included modularization in math courses through My Math Lab computerized learning. Second, the college created a policy whereby students whose scores indicated they needed to be placed in developmental reading writing or math could not register late. The third strategy was in the area of support and provided for the strategic objective known as avoidance, in which students are advised to avoid certain courses that will not lead to their academic progress. In this particular case, the strategy type was one of support in the area of preparation for the placement test.

Eastern Gateway Community College implemented four new strategies as part of their developmental education initiative. The first three instructional strategies were focused on accelerating students' progress through the sequence of developmental education courses and included a redesign of those courses. The instructional strategy included the integration of low-level developmental education with the adult basic education program at the college. Finally, Eastern Gateway created a policy to mandate that students complete developmental education requirements before proceeding to college-level courses. All four of the strategies implemented by Eastern Gateway community college were new to the college.

El Paso Community College created three strategies as part of their developmental education initiatives. Two of the strategies were new to the college, the first being an instructional strategy to accelerate the students' progress through a self-paced computerized math emporium. The second new strategy provided student support through a case management system of intensive tutoring and other services. The third strategy was a scaled-up version of a current developmental education strategy that provided support through pretesting, test prep before placement testing, and orientation.

The objective behind the strategy was to allow students to avoid taking developmental courses if possible and shorten their time in college coursework.

As part of their developmental education initiative, Guilford Technical Community College implemented three strategies all in the area of support. Two new strategies included online or in-person review for the college placement test. The objective of the strategy was to allow students to avoid taking developmental education courses and move directly into college-level courses. A second new strategy, also in the area of support, provided intensive case management for students who were placed into two or more areas of development lunch. A final strategy provided a scaled-up support of a current student orientation, advising, and registration program for students placing in two or more areas of development education. This program was expanded as part of Gilford's developmental education initiatives (Quint et al., 2013).

Housatonic Community College's strategies for their development education college initiative were all in the area of instruction. Two of the strategies were scaled-up versions of current programs and included modularized sections of both algebra and prealgebra. The modules allowed students to stop in and stop out of the course and take only those modules that related to tasks for which the students needed extra help. A third instructional strategy, also an accelerated strategy, was to create a modularized open-entry open-exit English offering (Quint et al., 2013).

Houston Community College capitalized on three existing strategies and sought to scale up their current offerings. Two of those offerings were in the area of support, the first of which was to mandate a freshman success guided studies or GUST course for all first-time students. The objective behind the strategy was to offer additional support to learners. The second strategy in the area of support was an 8-week math bridge course to help students whose scores were on the cusp to move up a full developmental level. This accelerated strategy allowed for students to complete their developmental course work in 8-weeks and continue into college-level courses. The final strategy at Houston Community College was a scaled-up instructional strategy that provided additional support through a learning community environment, which linked the guided studies course to a developmental math and developmental English course (Quint et al., 2013).

North Central State College developed four new strategies as part of their development education initiative. Three of the four strategies were in the area of support. Two of those support strategies were scaled-up versions of current strategies and focused on the expansion of tutoring in writing and math. A third strategy in the area of support was a scaled-up strategy to allow students to avoid taking needed developmental education course work. The college implemented a 1-week fast track math boot camp, during which students would take an intensive math courses and shortened time periods. The fourth strategy implemented by North Central State College was a policy change that required a redesign of the assessment and placement process, including cut scores or cut points for developmental placement (Quint et al., 2013).

Norwalk Community College focused their efforts on one instructional, scaled-up support. They developed a learning community which paired an upper level developmental writing course with a student success course. The plan behind the learning community was to provide additional support to learners as they took a developmental course (Quint et al., 2013).

Patrick Henry Community College instituted two scaled-up instructional strategies. The first was an accelerated strategy fast track, which paired the highest level developmental course with a college-level course. The Objective of the next instructional strategy was to provide instructional relevance and approaches that altered the curriculum or instructional modality to make the course more engaging to students. The third strategy implemented by Patrick Henry Community College was in the area of support and provided for a scaled-up, enhanced advising preprogram and included the creation of a student database to identify high-risk students and enhance the continuity of care across the advising staff (Quint et al., 2013).

The three new developmental strategies developed by Sinclair Community College included a high school early support program made up of case management in eight high school college and career centers. The two additional strategies developed by Sinclair Community College were both instructional accelerated programs. The first, developmental math modules and boot camp and the second, an accelerated learning program paired highest level developmental English course with a college-level English course. In both cases the purpose of the instructional accelerated programs was to speed up the amount of time a learner needed to stay in the developmental education sequence (Quint et al., 2013).

South Texas College implemented three new developmental strategies as part of their developmental education initiative. The first two strategies were scaled-up support strategies in case management. Both of the strategies impacted reading and English students, one through face-to-face methods and one through an email and phone project. The third strategy was a new instructional strategy with the objective of instructional relevance approaches that alter the curriculum or instructional modalities and make courses more engaging to students. In this case, South Texas College created a program of contextualization in developmental reading and English curriculum (Quint et al., 2013).

Valencia College expanded on three existing strategies, the first in the area of instruction. Valencia created learning communities by pairing developmental courses and student success courses. The intent was to provide additional support through the learning community environment. The second strategy was in the area of support and provided for supplemental learning, or peer-to-peer facilitated learning in the classroom. The final strategy type was a high school strategy which offered a bridge program, scholarships, and intensive support for 250 high risk low income high school students (Quint et al., 2013).

Finally, Zane State College developed two new instructional strategies as part of their developmental education initiative. The first was an accelerated program, which paired and compressed DMC; the second instructional strategy altered curriculum or instructional modalities to make courses more engaging for greater instructional relevance. The new instructional strategy included pairing developmental reading and English courses with college-level courses. The final support implemented by Zane State

College was a scaled-up version of an existing support, including scaled-up advising for students (Quint et al., 2013).

Figure 4 demonstrates the distribution of the strategies implemented by the 15 colleges who participated in the Developmental Education Initiative. The bar graph seen in Figure 4 demonstrates the outcome differences by strategy and strategy objective. In some cases, the difference made by the strategy was minimal.

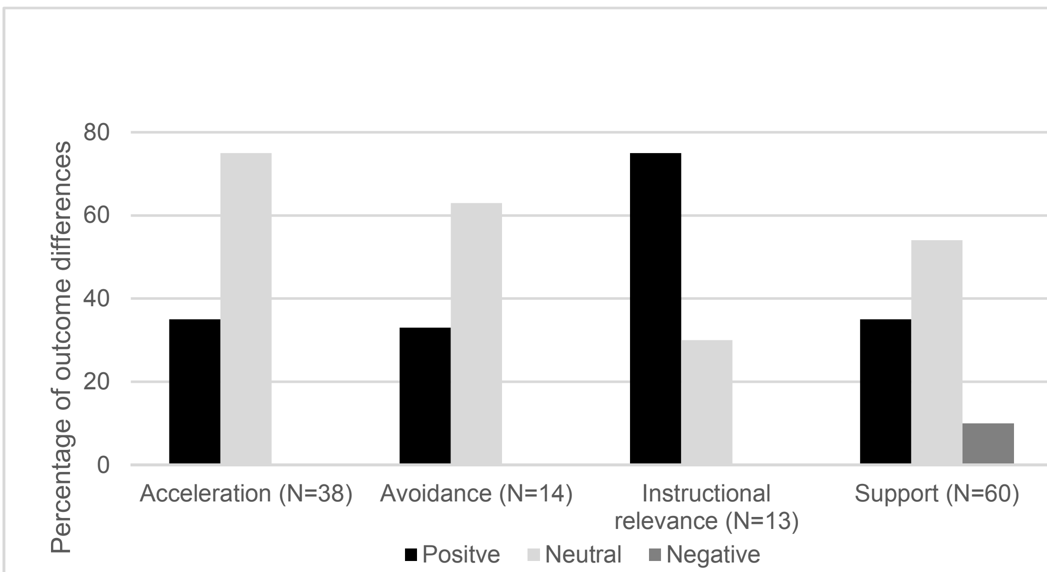

Figure 4. Outcome differences associated with participation in DEI focal strategies. Sorted by strategy objective and whether the difference is positive, neutral, or negative. The figure shows outcomes associated with participation in the focal strategies; it cannot be inferred that participation caused these outcomes (Quint et al., 2013).

As is evidenced in Figure 4, the majority (27%) of the initiatives instituted by the 15 colleges that were a part of the Developmental Education Initiative were in the area of course computerization, modularization, compression, and individualization. In other words, the majority of the strategies used were accelerated and self-paced strategies. The next largest category of support strategies (25%) includes intense advising and mentoring using a case management model (Quint et al., 2013). Figure 4 also demonstrates that in all the strategies and strategy objectives, the area of instructional relevance made the most difference in learner outcomes.

Finally, Table 7 provides the outcome differences based on the learners' participation in various strategies implemented in the Developmental Education Initiative.

Table 7

Outcome Differences Associated with Participation in DEI Focal Strategies

	Percentage of Focal Strategies for Which Outcome Difference Is:				Number of Strategies for Which Outcome Was Measured
Outcome Measured	Positive	Neutral	Negative	Total	
First-term outcomes					
Credits earned in first term	45.2	45.2	9.6	100.0	31
GPA at end of first term	29.0	67.8	3.2	100.0	31
Second-term outcomes					
Persistence to beginning of second term	28.6	67.9	3.5	100.0	28
Passed gatekeeper English by end of second term	50.0	50.0	--	100.0	18
Passed gatekeeper Math by end of second term	29.4	64.7	5.9	100.0	17
All Outcomes	36.0	59.2	4.8	100.0	125[a]

Note. The table shows outcomes associated with participation in the focal strategies; it cannot be inferred that participation caused these outcomes.

[a]This table represents the total number of times that the 31 focal strategies were counted in measuring the outcome differences for all first-term and second-term outcomes considered together (Quint et al., 2013).

The results shown in Table 7 indicate that beyond the first semester of a developmental students' academic career, an increased number of success strategies instituted to assist developmental learners does not necessarily equate to increased success.

Summary and Conclusions

In the aggregate, then, the research suggests mixed outcomes for redesigned and innovative approaches in developmental education. However, the relatively understudied nature of redesigned courses in developmental education, and especially mathematics, points to the importance of this study. Moreover, major theories in education have long included stereotype threat based on gender and ethnicity as possible factors persistent from K-12 and into the college setting, yet these phenomena too remain understudied, especially in developmental education. Thus, the technology DMC courses at MCC provide a rich data pool from which to develop a quasi-experimental design with the primary focus on the efficacy of technology DMC. If the technology DMC in general promote greater student success, then they may also promote positive student identities. The data also provide insight as to the degree, if at all, that age, gender, and ethnicity may further affect these identities, as will be explained with regard to the research questions and hypotheses in Chapter 3.

Chapter 3: Research Method

The purpose of this quantitative quasi-experimental study was to investigate the difference in the course completion rates between students in traditional teacher DMC and the technology DMC while predictor for age, gender, and ethnicity. Research must still investigate the best approaches to developmental education to ensure high student success rates because many developmental education programs continue to experience major student retention and graduation problems. The predictor variables help shed light on factors that may be connected to course type, which may further reinforce a need for developing instructional awareness programs in potential teacher biases or content delivery methods.

Chapter 3 of the study will provide details of the research methods including an overview of the setting. An overview of the setting will be followed by details of the research design and a rationale for that design. The methodology of the study addresses population, sampling procedures, data collection, instrumentation and operationalization of constructs, data analysis plan, threats to validity, and ethical procedures. Finally, Chapter 3 ends with a summary.

Research Design and Rationale

Per the focus of the study, course completion rates were the dependent variable. The independent variables of course design type, whether teacher DMC or technology DMC, were the focal independent variable for this research; age; gender, and ethnicity were predictor variables. The variables were coded in standard numeric format for statistical evaluation, with none of the categorical variables possessing qualities of ordinal variables. In other words, the dependent variable is a numeric variable course completion rates and the independent variables course type and gender are all binary or dichotomous variables. In accord with binary logistic regression, the dependent variable then is binary. Ethnicity is a nominal categorical variable. In other words, the numeric values attached for statistical evaluation simply become identifiers with each coded version of ethnicity included in the model except for a default. Age is the only variable with a numeric value that will have any comparative meaning in a continuous or ordinal sense; in this case, it is a continuous integer. The rational for using this design is based on the different operationalizations necessary due to the variable types. With a continuous integer like age along with both a nominal categorical variable and multiple binary variables, binary logistic regression models adequately manage the variables to demonstrate predictive ability through statistical significance.

The research questions were designed to determine whether there is a significant difference between the teacher DMC and technology DMC in developmental education. Additionally, the independent variables of age, gender, and ethnicity were added due to the possible effects of technology literacy and/or stereotype threat. Figure 5 illustrates the area of focus in Tinto's retention model as well as how the research questions from Chapter 1 after the figures relate to the retention model.

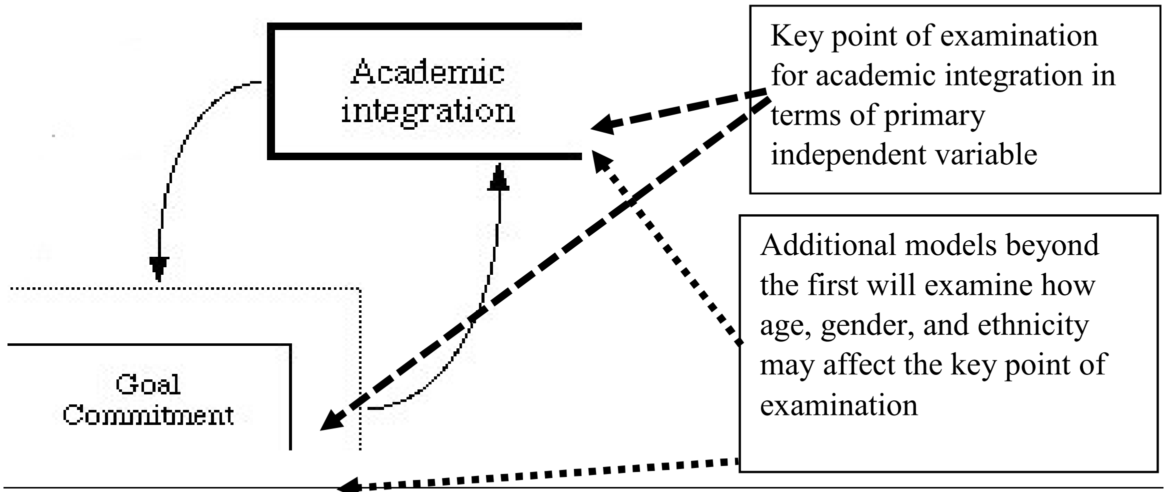

Figure 5. Focal points of Tinto's theory of retention. From "Tinto's model of student retention," by S. W. Draper, 2008. Retrieved from http://www.psy.gla.ac.uk/~steve/localed/tinto.html

I conducted all the statistical tests and analyzed all the data in a quasi-experimental design. The primary research question regarding the effect of technology DMC on completion rates of students in mathematics courses was tested with binary logistic regression, which due to its nature can function much like a regression version of a *t*-test often used for experimental designs. For binary logistic regression, the dependent variable should be dichotomous, and these data meet that assumption. The independent variable for the primary research questions is also dichotomous, which fits within acceptable parameters for binary logistic regression.

Methodology

Population

The ideal target population is all community college students in developmental education mathematics programs in the United States. However, due to the nature of the sample, discussed in the next section, the population may be more appropriately constrained to Midwest community college students in developmental education mathematics programs. The limitation derives from the nature of using data for students in DMC at MCC.

The population from MCC used as a convenience sample consists of approximately 2,900 college freshmen whose computerized placement test scores indicated the need for remediation and were enrolled in either a teacher DMC or a technology-directed developmental mathematics course. The convenience sample, discussed in more detail in the next section, of over 2,900 students was drawn from the academic years 2010-2015. All students who were enrolled in a teacher DMC or technology DMC during the academic years of 2010-2015 were included in the study.

Sampling and Sampling Procedures

This quantitative study was conducted using data from MCC. MCC offers over 80 programs of study to over 6,000 credit students and serves an area where only 20% of the population have a bachelor's degree compared to nearly 30% for the nation (U.S. Census, 2016). According to the college's office of research, sixty percent of MCC's student population are first-generation college students, and nearly 90% require some time of remediation before entering regular college courses. As already mentioned in Chapter 1, these demographics contribute to the limitations of generalizability, a topic broached again later in this chapter. It is worth mentioning here because the data regarding the postsecondary educational degree attainment of the population overall in the area gives some idea of locales to which the research findings may be of use to researchers seeking to conduct further tests of community college developmental education programs in the Midwest based on this study's findings.

The population of students at MCC served as a weighted, biased sample for community college students in development education. The determination to favor a quantitative study derived from the realization of insights that can be gleaned in the amount of data available. Because there are data on over 2,900 students, there should be adequate data to run the various tests. As the courses that were used in the study have already been completed, there are no known resource or time constraints consistent with the design choice. Generalizability may be further restricted to other areas with similar educational demographics and challenges in their developmental education mathematics programs.

Procedures for Recruitment, Participation, and Data Collection

MCC provided the data for the study through their office of institutional research. The data for this study does not include personal identifiers and be limited to only the variables of course completion rates, course design, age, gender, and ethnicity. Upon receipt of the 6 years of data, I began the testing process. No students needed to be recruited for participation, and students were not be given informed consent. Because of the lack of personal identifiers in the data, student anonymity should result in a risk-free study. The students did not be an active part of the study. The data were not disaggregated; therefore, there was no risk of identification.

Archival Data

MCC agreed to share all data from years 2010-2015 that relate to this study. The data are currently stored in MCC's data system, and only the variables included in this research will be shared by MCC. These data were compiled in an Excel spreadsheet for my use by an MCC employee.

Instrumentation and Operationalization of Constructs

The exploratory variables of age, gender, and ethnicity are consistent with operationalizations used in social science research in general. In other words, self-reported age, gender, and ethnicity as recorded in the MCC student database will be coded appropriately. Age will be a continuous variable. Gender and ethnicity will be coded as nominal categorical variables. All of these independent variables, however, are tangential to the primary research question of the efficacy of technology DMC when compared to teacher DMC in student completion rates.

Neither the primary independent variable nor the dependent variable, or course type and completion rate respectively, use any kind of instrumentation. Technology DMC are those in which MCC shifted to greater technology emphasis for student learning in 2012 through to the present. Teacher DMC are those in which MCC utilized teacher DMC almost exclusively prior to 2012. Completion rate is either a pass or fail grade because continuous test scores or grades are not available for the developmental education mathematics courses. Although a continuous test score or grade would be preferable, the data overall provide an opportunity to begin to explore the effects of course type on completion rates in an understudied phenomenon even given the variable limitations.

Data Analysis Plan

MCC provided the data in an Excel spreadsheet with only the following variables included: course completion rates, course design, age, gender, and ethnicity. The data from the Excel spreadsheet were uploaded into the Statistical Package for the Social Sciences (SPSS). Statistical tests were conducted based on the research questions already stated earlier in this chapter. The data set from the first 3 years of the study is approximately 2500, which represents a control group of pooled panel data with students in teacher DMC. The data set from the last 3 years is approximately 400, which represents an experimental group of pooled panel data with students in technology DMC, or the variable introduced distinct from the control group.

Using binary logistic regression on the primary research question simplified the process for the remaining hypotheses because logistoc regression facilitated the use of a stepwise exploratory approach, with each additional predictor variable added in separate models after the primary research question. Stepwise model testing proves most useful when research explores an uncertain directional nature of a hypothesis as opposed to research with a predisposed directional expectation for a hypothesis. In other words, based on the literature review, the primary independent variable of mathematics course type as well as all of the predictor variables should have some kind of effect on the completion rate dependent variable, but the nature of that effect remains, or these effects remain, unknown.

The justification for using multiple models derives from the exploratory nature of the research. If interaction effects were found to exist, then appropriate interaction effect variables would have been introduced. The Threats to Validity section outlines additional tests to avoid the pitfalls of covariance as well as to ensure that the population conformed as closely as possible to characteristics one would expect in a random sample.

Unlike linear regression, logistic regression does not rely on a goodness of fit statistic. However, a pseudo R^2 statistic can be included (McFadden, 1974). The statistic R^2 is still not a totally reliable indicator of a model's appropriateness and should only be used as a guide along with variables consistent with literature and theory, even in exploratory research. In the aggregate, though, the use of R^2 in conjunction with multiple models, evaluation of potential covariance, and examination of changes in standard error ranges can provide insight into how the variables may be acting in real-world manifestations.

Threats to Validity

As in any research design, the appropriate operationalization of variables presents the most serious threat to validity. In other words, do the quantified statistical values actually represent the real-world manifestations intended to be observed in the research? For this study, the primary research question and its variables seem very valid and reliable. Whether or not a student successfully completed a course is measured by pass or fail. Course design type, based on the course title and numbers available in the MCC data set, divides all courses into a classification as either a teacher DMC or a technology DMC. There are some hidden threats to validity within these rather straightforward variables though. Variation across specific syllabi, if not standardized by the college; classroom dynamics, which to some extent can be tapped by the additional independent variables of age, gender, and ethnicity; and teaching styles or methodologies could all affect an objective evaluation, or the validity, of both the dependent variable and independent variable in the primary research question. However, the data do include course number identifiers, which allow for distinguishing between course section-based variance if the data seem somehow compromised along these lines.

In terms of the other independent variables and their operationalization, age is clearly an easily tapped and accurate operationalization of an individual's age. The same can be said for gender, but ethnicity can be a more complicated variable. Essentially, in most cases, the social effects of gender will be overall consistent in population interactions with the variable based on subject self-reporting. Stated another way, if a person checks the male box or female box for gender, then it is generally also probable that most people who encounter that person will similarly acknowledge the same gender classification. Ethnicity, on the other hand, is a much more fluid variable and may be less valid in terms of tapping a phenomenon within a classroom without also involving classroom observation or qualitative analysis. Using the ethnicity variable can at least provide insight in exploratory research such as this. For example, in stereotype threat scenarios, it is often the individual self-perception that triggers the stereotype threat rather than any interaction with others. Nonetheless, evaluation of the data in terms of ethnicity and its effects should proceed with caution due to these factors.

To help further examine the data, variance inflation factor tests can evaluate whether the predictor variables have high levels of covariance with each other or the primary research independent variable. Basically, one would expect there to be some level of covariance between the dependent variable and independent variable or else there would be little point to propose a hypothesis and run tests. One does not want high levels of covariance between independent variables without accounting for it with interaction-effect variables if such are necessary. Thus, the use of VIF tests ensures the integrity of each model.

Ethical Procedures

After receiving Walden University's IRB approval, number M01-02-18-0042741CC, MCC agreed to release data for use in this research. MCC provided an Institutional Review Board Request Form, with no specific document number identifiers but otherwise appropriately signed by necessary parties, for the data release. Other than preserving anonymity of the students in the data provided by MCC, no other ethical concerns seem germane to the project. Thus, the students in the data are protected because the students are not named, nor are they identifiable by any other means. The data for this study will be collected and stored on a laptop computer, with all of the data also backed up at MCC. Data from the study will be destroyed one year after the study is complete.

Summary

Chapter 3 described the setting MCC for the purpose of this study. The shift in the DMC course design allows for a quasi-experimental design, but extending generalizations of the findings beyond MCC would be problematic. Nonetheless, the results specific to MCC can be useful for other educational institutions to evaluate their DMC. Because no actual original data were gathered, the data are secondary data provided by MCC with all proper procedural guidelines followed for use in a quasi-experimental design to investigate potential effects of technology DMC on course completion rates as well as the potential effects of age, gender, and ethnicity, in conjunction with technology DMC, on course completion rates. Essentially, due to the nature of secondary data in general and because this study did not directly engage research subjects, standard IRB clearance from Walden University along with clearance with MCC's IRB provided the necessary authorization to access the data. The greatest concern to validity seems likely to emerge from any possible unknown and undocumented interaction effects that may occur between the independent variables. The next chapter, Chapter 4, details the specific diagnostic tests used to evaluate the data for heteroscedasticity and multicollinearity along with the results of the models used for the research questions.

Chapter 4: Results

The purpose of this quantitative study was to compare completion rates in DMC of over 2,900 MCC students in teacher DMC and technology DMC. The research questions and hypothesis are as follows:

RQ1: What is the difference in student course completion rates between teacher DMC and technology DMC at MCC?

$H_1$1: There is a significant difference in student course completion rates between teacher DMC and technology DMC.

$H_0$1: There is no significant difference in student course completion rates in teacher DMC and technology DMC.

RQ2: What is the difference in student course completion rates between teacher DMC and technology DMC at MCC when controlling for age?

$H_1$2: There is a significant difference in student course completion rates between teacher DMC and technology DMC when controlling for age.

$H_0$2: There is no significant difference in student course completion rates in teacher DMC and technology DMC when controlling for age.

RQ3: What is difference in student course completion rates between teacher DMC and technology DMC at MCC when controlling for gender and ethnicity?

$H_1$3: There is a significant difference in student course completion rates between teacher DMC and technology DMC when controlling for gender and ethnicity.

H_0: There is no significant difference in student course completion rates between teacher DMC and technology DMC when controlling for gender and ethnicity.

With the introduction of the chapter having reiterated an overview of the purpose, research questions, and hypotheses, the sections that follow delve directly into the data. The first section, Data Collection, provides details on the acquisition of archival data from MCC. Coding, descriptive statistics, and demographic data characteristics of the sample are also detailed in the Data Collection section. The second section, Results, first includes data diagnostic tests before turning to the results of the logistic regressions.

Data Collection

MCC provided the data, so no data collection occurred beyond procurement of secondary data. The MCC statistician cleaned the data to include only the information relevant to the research questions. The data, shared via an Excel spreadsheet, consisted of the following fields: Enrollment Term, Enrolled Course Name, Enrolled Course Section Number, Student No., Success, Person Gender, Person IPEDS Race/Ethnic Description, Age During Class, Person Age, and Instruction. Enrollment Term, Enrolled Course Name, and Enrolled Course Section Number were not relevant beyond confirming the course type, whether a teacher DMC or a technology DMC per the research design. Thus, they were removed from the data analysis portions of the data treatment and not included in the descriptive statistics. Of the two variables reporting student age, Age During Class remained part of the research design because it captures age at the time of the student's enrollment in the course.

Success, Person Gender, Person IPEDS Race/Ethnic Description, Age During Class, and Instruction were the data fields used for the data analyses. Student No. also continued to be useful as a unique identifier for each case. No risk for revealing specific identities exists with the Student No. variable because it is a discrete number not affiliated with a student identification number or in any other way a permanent indicator of student identity. To remain consistent with the variable labels developed for this research project, each of the fields was renamed and recoded when appropriate. Additionally, the data did not have any missing data or empty cells in the 2,987 cases in the data set, but some issues in the data were addressed as explained in what follows.

Coding for data analysis and descriptive statistics of the data appear next in this section of the chapter, whereas data diagnostics appear at the beginning of the Results section. Success, or whether the student passed or did not pass the course, was labeled Completion Rate. Success was already coded as a binary or dichotomous variable, with 0 indicating a student did not pass the course and 1 indicating a student passed the course, in every cell with no ambiguous entries. No recoding was necessary for Completion Rate. Person Gender, also a binary or dichotomous variable, was either F for female or M for male in the data set. The only change to the label was to shorten it to Gender only; every F or female entry was recoded as 1, and every M or male was recoded as 0 for statistical analyses. The cells had no ambiguous or subjective information. Age During Class also had complete and unambiguous data in the form of a two-digit entry for age in every cell, thus resulting in only the shortening of the label to Age. The other variables included some slightly more complicated recoding and treatment decisions, detailed hereafter.

A total of nine ethnicity descriptors appeared in the data field Person IPEDS Race/Ethnic Description: White, Unknown, Two or More Races, Non-Resident Alien, Hispanic, Hawaiian/Pacific Islander, Black or African American, Asian, and American Indian. Because of the ambiguity of the descriptors Unknown and Non-Resident Alien, those cases were dropped, resulting in a loss of a total of 244 cases. The remaining descriptors generally posed no serious problems, but Hawaiian/Pacific Islander only included eight cases. As a solution and consistent with much demographic reporting of ethnicity, the Hawaiian/Pacific Islander category was merged with the Asian category for a total of 39 cases. Finally, regarding the data field label, it was renamed simply Ethnicity per the research design labels. Otherwise, the descriptors for the Ethnicity field remained the same as the Person IPEDS Race/Ethnic Description.

Instruction contained the type of course for each student case. This variable was carefully evaluated before cases were dropped, though ultimately another 209 cases, after the data treatment made by removing cases due to the Ethnicity variable, were dropped due to the Instruction type indicated. The full, complete data field entries were as follows: Traditional Face-to-Face, Online, ALEKS, College Math Prep, and one other descriptor similar in nature to College Math Prep but specific to the college and region. Thus, that specific descriptor was not stated here to help maintain MCC's confidentiality though the descriptor was essentially treated as College Math Prep. College Math Prep and the unstated descriptor were dropped because they did not clearly fit within the research design and numbered below 30 total cases. The Online field identified courses in the curriculum that were conducted online before the technology DMC were provided at the college, a kind of online design that did not privilege ALEKS in place of the instructor. To prevent complicating the interpretation of the data due to the nature of how some may observe unclear boundaries between Online courses and the ALEKS courses, the Online course cases were dropped as well. The data set still contained 2,534 cases, with 2,059 that fit the teacher DMC type per the research project specifications and 475 that fit the technology DMC type per the research project specifications. Therefore, Traditional Face-to-Face courses were recoded as Traditional, and ALEKS courses were recoded as Redesigned Course Type. The Instruction field was changed to Course Type.

Table 8 provides details on all the variable frequencies except Age, which is graphically described in a histogram in Figure 6. Table 9 reports the mean, median, mode, range and standard deviation for all variables for all students in both the teacher DMC and the technology DMC.

Table 8

Frequencies for all Variables (n = 2,534)

Variable	Coded Values	Frequency
Completion Rate	0 (Did not pass)	1,271
	1 (Passed)	1,263
	Total	2,534
Gender	0 (Male)	877
	1 (Female)	1,657
	Total	2,534
Ethnicity	0 (White)	1,753
	1 (Two or More Races)	81
	2 (Hispanic)	410
	3 (Asian)	39
	4 (Black/African American)	150
	5 (American Indian)	101
	Total	2,534
Course Type	0 (Traditional Course)	2,059
	1 (Redesigned Course)	475
	Total	2,534

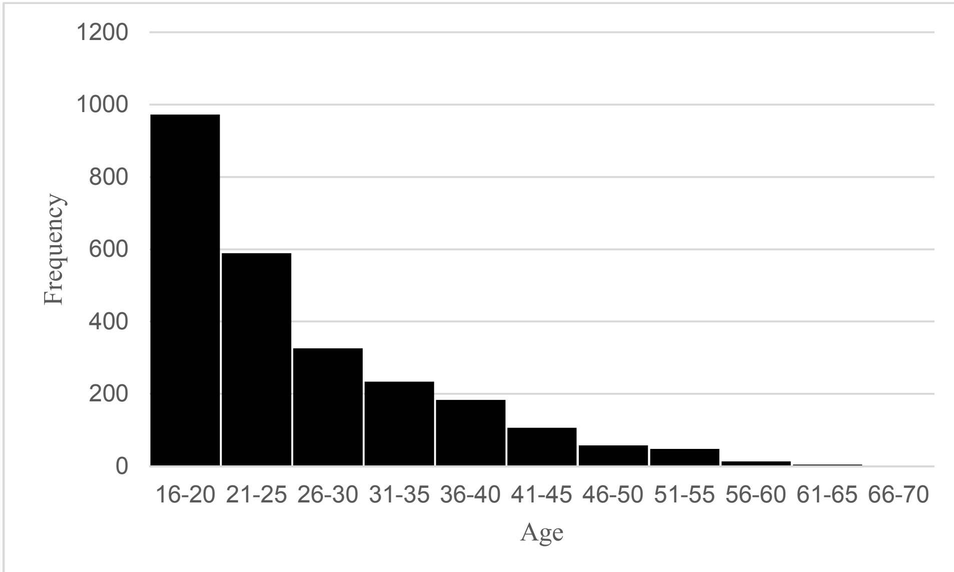

Figure 6. Age frequency.

Table 9

Descriptive Statistics for All Variables (n = 2,534)

Variable	Mean	Median	Mode	Range	Standard Deviation
Completion Rate	0.4984	0	0	0, 1	0.500096195
Gender	0.6539	1	1	0, 1	0.475817215
Ethnicity	0.9021	0	0	0, 5	1.607047312
Age	26.1066	23	18	16, 66	9.098947919
Course Type	0.1875	0	0	0, 1	0.390349905

As is evidenced in Tables 8 and 9, Completion Rate is almost an exact balance of 0s and 1s, which indicates a nearly perfect binomial distribution. Gender is also a binary variable F (Female) or M (Male) in the data set. Gender is slightly skewed with a ratio of approximately 2:1 for female to male. This shows many more females in the developmental math program than males, but in general this is consistent with college enrollment overall. The nonwhite population of students at MCC in the developmental math program is larger than many other Midwest community colleges in general at approximately a third of the students; MCC is more diverse than many Midwest community colleges with its student demographics being comparable to many other national community colleges in level of diversity. Finally, the age of students shows a generally nontraditional average age of 26 or greater, though the mean stands at 23. About half of the students, then, fit into the nontraditional category of students, which again appears consistent with trends at community colleges overall.

Results

Two key tests of the normality of the data were conducted to aid in the interpretation of the statistical tests: Glejser test for heteroscedasticity (GTH) and variance inflation factors (VIFs). GTH identifies variables with variance that may be outside of expected parameters for the model specifications, but just because the variable indicates a significant GTH value does not necessarily deem it inappropriate for a model if the model was specified with such expectations (Berry & Feldman, 1985; Glejser, 1969). VIFs also represent important diagnostic tools in determining whether independent variables have high degrees of co-variance or collinearity (Hair, Anderson, Tatham, & Black, 2006). The diagnostics follow in Table 10 for GTH and Table 11 for VIF. The dependent variable was excluded from the testing because the assumption of any statistical test is that there may be some kind of co-variance and/or unusual biases between the dependent variables and the independent variables, hence the purpose of statistical significance tests of independent variables.

Table 10

Glejser Test for Heteroscedasticity

Variable	*B*	SE *B*	B
Technology DMC	0.001	0.005	0.795
Age	0.000	-0.024	0.198
Female	0.007	0.037	0.046*
Mixed	0.096	0.181	0.000***
Hispanic	0.003	0.013	0.479
Asian	0.009	0.012	0.525
Black	-0.040	-0.102	0.000***
American Indian	-0.214	-0.401	0.000***

Note. *** = significance equal to or less than 0.001, ** = significance equal to or less than 0.01, * = significance equal to or less than 0.05

Table 11

Variance Inflation Factors

Variable	Tolerance	VIF
Technology DMC	0.922	1.084
Age	0.981	1.019
Female	0.982	1.019
Mixed	0.864	1.158
Hispanic	0.935	1.069
Asian	0.986	1.014
Black	0.967	1.034
American Indian	0.834	1.199

With regard to the independent variables of Female, Mixed, Black, and American Indian, GTH comparisons between unstandardized and standardized coefficients indicated statistical significance. However, that alone does not necessarily indicate that the data do not conform to expectations. According to assumptions in the theoretical foundations for the exploratory aspects of the tests beyond only the test of whether Technology DMC affect Completion Rates in developmental mathematics when compared to Teacher DMC, one might expect to see fairly dramatic differences between standardized and unstandardized coefficients. In effect, one would expect the unstandardized coefficient to demonstrate some degree of abnormality when compared to a standardized coefficient. Nonetheless, due to the exploratory nature of the inclusion of those variables, reporting of results and interpretation must proceed with caution. No collinearity appears to be present in the data with all the VIF values hovering around 1.

This section now transitions to model equations representative of the logistic regressions prior to inclusion of the model outputs relative to each research question. In its simplest form, the predictive equation related to Research Question 1 for developmental mathematics course completion rates can be represented as follows.

$$Y_{i,t+1} = BX_{i,t}$$

The simple model relates to Hypothesis 1, where Y is the Completion Rate for developmental mathematics courses, or more accurately individual degree of success for each iteration in the model, and X is the Course Type, whether Teacher DMC or Technology DMC. Because the hypotheses and research questions were already restated at the beginning of the chapter, they are not reproduced again here. The remainder of this section simply details the predictive equations before the model outputs are discussed.

For Research Question 2, the inclusion of Age expands the equation as follows.

$$Y_{i,t+1} = BX1_{i,t} + BX2(Age)_{i,t}$$

The only real change in the equation can be seen in the denotation of an additional potential predictive variable. As stated before, the equation has been included both due to gaps in research involving possible age-related technology literacy in mathematics course and for exploratory purposes for future research; however, interpretation of the equation and the statistical outcomes must be made with caution. The dependent variable *Y* remains the same in Completion Rate. The first independent predictor of Course Type includes the identifier of *X1* for Course Type, and the second potential independent predictor variable of *X2* includes Age.

Research Question 3 focuses on Gender and Ethnicity, so Age was dropped from the model until being reintroduced in the final full model. Thus, like with Research Question 2, the variables have been stated in an equation with numeric coding to disambiguate the the primary independent variable from the predictors.

$$Y_{i,t+1} = BX1_{i,t} + BX2(Gender)_{i,t} + BX3_{a,b,c,d,e}(Ethnicity)_{i,t}$$

Unlike Research Question 2, the additional potential predictor variables are all categorical. Thus, it is important to state the default against which the modeled variables have been tested as well as the meaning of the subscript following *X3*. The variables *Y* and *X1* remain the same in their representation of Completion Rate and Course Type, but *X2* now represents Gender. In the statistical test, the default against which the Gender variable has been tested is Male, so the variable reported in terms of statistical significance is Female.

In terms of *X3*, it is a categorical variable for Ethnicity. As explained in the descriptive statistics, the coding process resulted in 6 total Ethnicity categories, with White coded as 0. In the initial descriptive coding, each category was assigned a value beyond 0 through to 5, but for the statistical test, each Ethnicity was coded as its own dummy variable for inclusion in the model. Hence, the subscripts following *X3* all respectively refer to the 5 coded categories for Mixed, Hispanic, Asian, Black, and American Indian, with White as the default against which all categories were tested. Although not relevant to a specific hypothesis included in the research design, a full model was also evaluated to attempt to discern any substantive changes to potential predictors when all variables were included. Ultimately the primary goal of the research project was to evaluate the effects of the primary independent variable Course Type on Completion Rates, per Hypothesis 1, but for future research possibilities, the richness of the data was too valuable to ignore an opportunity for exploration of gaps in research identified in age-related technology literacy and possible stereotype threat phenomena in developmental mathematics courses where a shift to technology had occurred. The equation for the full model simply includes all of the former variables together, with Gender and Ethnicity now assigned to *X3* and *X4*, respectively.

$$Y_{i,t+1} = BX1_{i,t} + BX2(Age)_{i,t} + BX3(Gender)_{i,t} + BX4_{a,b,c,d,e}(Ethnicity)_{i,t}$$

With diagnostics and the model equation specifications stated, each model output result is now reported. It is important to further clarify why the model results have been reported with statistical significance values at .025, .01, and .001. Because the research questions are nondirectional in an exploratory design to primarily evaluate whether Technology DMC affect Completion Rates in developmental mathematics courses when compared to teacher DMC, each tail of the test should include .025 or 2.5% probability to account for a standard total of .05 or 5% probability that the results would not occur by randomness alone, or what is generally termed statistical significance.

Table 12

Completion Rates Regressed on Course Type

	Coefficient	Standard Error	*n* 2,534 R-squared 0.004 *p*-value
Constant	-0.061	0.044	
Technology DMC	0.294	0.102	0.004**

Note. *** = significance equal to or less than 0.001, ** = significance equal to or less than 0.01, * = significance equal to or less than 0.025

Table 12 reports the results of Model 1. Technology DMC, when compared to Teacher DMC, do have a statistically significant effect on outcomes for Completion Rates, with the *p*-value at 0.01, or 1%, probability.

Table 13

Completion Rates Regressed on Course Type and Age

	Coefficient	Standard Error	*n* 2,534 R-squared 0.018 *p*-value
Constant	-0.661	0.127	
Technology DMC	0.349	0.103	0.000***
Age	0.023	0.004	0.001***

Note. *** = significance equal to or less than 0.001, ** = significance equal to or less than 0.01, * = significance equal to or less than 0.025

According to the Model 2 results in Table 13, Age has a statistically significant effect on Completion Rates in developmental education mathematics courses at a value of .001, or less than 1 tenth of a percent, probability.

Table 14

Completion Rates Regressed on Course Type, Gender, and Ethnicity

			n	2,534
			R-squared	0.037
	Coefficient	Standard Error	*p*-value	
Constant	-0.286	0.075		
Technology DMC	0.226	0.108	0.036	
Female	0.418	0.085	0.000***	
Mixed	-0.803	0.263	0.002**	
Hispanic	-0.073	0.112	0.517	
Asian	-0.034	0.327	0.917	
Black	-0.575	0.179	0.001***	
American Indian	1.189	0.293	0.000***	

Note. *** = significance equal to or less than 0.001, ** = significance equal to or less than 0.01, * = significance equal to or less than 0.025

The model for Research Question 3, per the results reported in Table 14, indicates that Technology DMC and Teacher DMC have no statistical effect on Completion Rate given the value of .036, or 3.6%, probability when Gender and Ethnicity have been introduced into the model. Finally, for the exploratory research aspect of the project, the final model in Table 15 includes all the variables. The justification for exploring the regression results below also relates to the very small value of the R^2 statistic in all the models, even if it is a kind of pseudo-statistic in a logistic regression. Per a calculation Cohen (1992) developed for effect sizes, the model pseudo R^2 statistic can be examined to compare all the models, a discussion of which occurs following Table 15.

Table 15

Completion Rates Regressed on Course Type, Age, Gender, and Ethnicity

			n	2,534
			R-squared	0.05
	Coefficient	Standard Error	*p*-value	
Constant	-0.886	0.143		
Technology DMC	0.27	0.109	0.013*	
Age	0.023	0.005	0.000***	
Female	0.411	0.086	0.000***	
Mixed	-0.785	0.263	0.003**	
Hispanic	-0.025	0.113	0.824	
Asian	-0.002	0.327	0.996	
Black	-0.584	0.18	0.001***	
American Indian	1.229	0.298	0.000***	

Note. *** = significance equal to or less than 0.001, ** = significance equal to or less than 0.01, * = significance equal to or less than 0.025

Per Cohen (1992), effect size can be calculated using the formula $R^2/(1-R^2)$. The effect sizes, rounded to the nearest thousandth per model, are 0.004 for Model 1, 0.0183 for Model 2, 0.038 for Model 3, and 0.053 for Model 4. Moreover, Cohen (1992) defined small, medium, and large effect sizes found via these calculations to be 0.02 as small, 0.15 as medium, and 0.25 as large. These effect sizes, especially for Model 1 and Model 2, provide concern for strong conclusive claims regarding the effective power of the models.

However, when looking at the coefficients for the variables alone, the coefficient for Age is exactly the same in Model 4 as it was in Model 2, while in both Model 2 and Model 3, the coefficient for Technology DMC changed considerably, with an increase of 18.7%in Model 2 and a decrease of 23.1% in Model 3. In contrast, the coefficient for Technology DMC lowered by 8.2% in Model 4. In other words, Model 1 and Model 4 show more similar effects from Technology DMC than Model 2 and Model 3 do in comparison to Model 1. Additionally, the effect size of Model 1 is only 0.004, below even the average small effect size threshold reported in Cohen (1992), while in Model 4 it at least crosses the reported threshold at 0.053 for the lower end of a medium effect size.

Summary

In conclusion, the data demonstrated no issues of concern when evaluated and coded for use in statistical tests. After cleaning the data, enough cases remained for the logistic regression models. The descriptive statistics indicated that the population of students in developmental education mathematics at MCC, acting as a convenience sample for exploratory research, did not deviate from community college populations overall even though well over half of the population was female. Such gender demographics are consistent in general with trends that have been developing over the last two decades in college populations. Even the ethnic diversity was consistent with broader national statistics for community colleges; however, as mentioned earlier, MCC is a more diverse institution than many other community colleges in the Midwest region. Finally, regarding descriptive statistics, students tended to fall into the nontraditional age range, with at least half of the students in their mid-twenties or older, which is also consistent with trends at community colleges.

With regard to data normality, diagnostic tests did not indicate any unanticipated deviation in the data or collinearity between the independent variables. Two of the three models specific to the research questions, or Research Question 1 and Research Question 2, revealed statistical significance for the primary independent variable in its effect on

Completion Rate, in both cases showing a positive statistically significant effect for Technology DMC. The third model for Research Question 3 did not indicate two-tailed statistical significance, but its results still warrant discussion in Chapter 5. Likewise, the final full model showed statistical results also worth discussion in the next chapter.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this quantitative study was to examine the effects of a switch from teacher DMC to technology DMC in developmental education mathematics courses at MCC because the body of research on educational outcomes in community colleges is characterized by a lack of research into technology's effects on learners. Moreover, per Tinto's framework, students who experience success early in their educational trajectories should integrate into the institutional culture and educational culture overall, reinforcing their sense of belonging within the institution and postsecondary education in general. This research was focused on academic integration in the form of student success or lack thereof in high-risk populations in developmental education mathematics programs, with the primary focus on technology's effects on completion rates. The primary research question was supplemented with examination of effects of additional predictor variables because stereotype threat and technology literacy may be further complicating students' attempts to gain momentum in iterations of academic integration.

Key findings from the study include the following:

- Technology DMC do have a statistically significant effect on completion rates at the .01 significance level when no other independent predictor variables are included.
- The predictor variable Age has a statistically significant effect on completion rates in developmental education mathematics courses at the .001 significance level while Technology DMC maintain statistical significance when both are included in a model.

- The primary independent variable Technology DMChas no statistically significant effect on completion rate at the .036 significance level when the predictor variables Ethnicity and Gender are included in a model.

The sections to follow include further elaboration on these key findings in relation to acceptance or rejection of the null hypotheses for the research questions. The exploratory aspects of the research are discussed briefly as well in the next section while transitioning to the section to follow: Limitations of the Study. After the findings and limitations, the third section introduces recommendations. Additional possible social implications appear in the fourth section Implications. After all these sections, a conclusion ends Chapter 5.

Interpretation of the Findings

Technology. The central guiding research question was focused on the introduction of technology to developmental education mathematics courses. Per the primary research question, the focus of the research centered on whether technology DMC affected student course completion rates, and if so, the kind of effect the quasi-experimental intervention created. According to the model results of Table 12 from Chapter 4, the technology DMC at MCC do have a statistically significant effect on completion rates at the .01 significance level. Thus, the null hypothesis can be rejected. According to the model, the Technology DMC variable indicates an improvement in completion rate chances for students in developmental mathematics courses at MCC.

Such a finding is important because colleges are beginning to incorporate the use of computer software into their developmental mathematics courses. Wladis et al. (2014)

determined that colleges are showing some success in using computer-aided software in their developmental programs; however, the research showed that the programs needed to be enhanced and could not only rely on the software itself as a means for successful completion of the course. Zientek (2015) cited researchers (Gavitt, 2010; Spradlin 2009; Taylor 2008) who concluded that students in three studies did not show more significant improvement in developmental courses when they were able to use computer software.

The results in Model 1 relative to Research Question 1 indicate that the Technology DMC variable shows significant improvement on Completion Rate when compared to the default Teacher DMC variable. Although coefficients should be interpreted cautiously in a quasi-experimental design, Model 1 shows a constant of -0.061 for Completion Rate with Technology DMC changing the constant to a positive value of nearly 0.28. In effect, fpr students in the Teacher DMC, the not-pass rate is a much more dominant, likely outcome—the value coded as 0 in Completion Rate—whereas the introduction of Teacher DMC significantly improves the odds of a pass outcome—the value coded as 1 in Completion Rate.

Age. As detailed in in Chapter 2, one possible issue with technology in education can be age-related technology literacy. The inclusion of age as an independent variable allows for the research to investigate how age may be related to Completion Rate outcomes as well, leading to Research Question 2 and the hypotheses. Therefore, as part of the exploratory aspects of the research, the effects of the continuous predictor variable Age, if any, were examined in a separate model.

At MCC, age has a statistically significant effect on completion rates in developmental education mathematics courses at the .001 significance level, thus rejecting the null hypothesis. Additionally, the effect is of a positive nature, so the older a student, the better the potential likelihood of a pass–completion rate in a teacher DMC. In effect, because teacher DMC is the default against which technology DMC is compared, the coefficient represents the likeliood increase per year of age for a student to pass the course, or about 0.023 likelihood improvement for each year of age. The improvement builds on a constant in Model of -0.661. Thus, the likelihood for a no pass outcome for students who are younger and without the intervention of technology are quite high.

The coefficient for age increases when technology DMC is introduced to the model, which suggests that the coefficient in Model 2 for Technology DMC of 0.349 is most dramatic in its benefit for younger students. Interpreted cautiously, the cutoff may be around 30 years of age because that is the age at which the coefficient for the variable Age begins to reach the same degree of benefit reported for technology DMC. H This is important at MCC because the age range is 50, with the youngest student age 16, and the oldest student age 66; additionally, the mean age is 26, which indicates that over half of the students may be within an age range where technology may have less pronounced benefit.

Research has shown that younger students are more likely to complete course work and graduate than older college students (Dasinger, 2013). Because the research does not engage in a long-term study of student graduation rates, the reasons for such outcomes go beyond the parameters of this research. However, early success in the classroom, per Tinto's (1975) theory, is an important possible vehicle for developing a successful academic identity, acquisition of which can also be facilitated via developing connections in the college community overall. Therefore, academic success for older students may be even more important because nontraditional students may have other obligations and responsibilities that interfere with deeper immersion in the college community.

Stereotype threat. There is also a significant gap in completion of developmental and traditional mathematics courses, or teacher DMC as defined in this study, among ethnicity and age groups (Stewart et al., 2015). Thus, Ethnicity was included in Model 3, along with Gender, due to the body of literature on stereotype threat, which relates to the exploratory nature of the research. These variables also relate to the final model and discussion. Both ethnicity and gender were included in the stereotype threat hypothesis in Research Question 3, though each of the two variables is discussed separately below..

Based on the way Research Question 3 is worded, the null hypothesis must be accepted in that Technology DMC and Teacher DMC have no statistical effect on Completion Rate given the value of 0.036, or 3.6%, probability. Mixed and Black students have worse Completion Rate, or greater not-pass rates, in a Teacher DMC than White students do. Additionally, Hispanic and Asian students appear to have no statistically significant differences in Completion Rate when compared to White students in a Teacher DMC while American Indian students appear to have better pass Completion Rates in a Teacher DMC than White students do. Due to a gap in research, no real substantive research has been directed toward exploring the possible effects of ethnicity in terms of stereotype threat and how technology may or may not mediate stereotype threat.

Gender is also included in the model, a point discussed further in the next section. However, in Model 3, the constant is -0.286 while the coefficient for technology DMC is 0.226. The difference between the coefficient and the constant is nearly the same as the original constant in Model 1 at -0.062. Although far from conclusive, it does generate a series of questions worth pursuing further in how Ethnicity may be a key variable in accounting for differences in Completion Rate in a Teacher DMC. This seems particularly relevant since the default comparison group is White students, and the difference between the coefficients and constants may suggest that a technology DMC may be of great importance as a mitigating variable for students of ethnicity who appear to struggle heavily in a teacher DMC, specifically Black and Mixed students with coefficients of -0.575 and -0.803 respectively.

Females have better pass completion rates all courses, whether a teacher DMC or a technology DMC, based on the model specifications in Model 3, but all of these must be interpreted carefully because the research design was not specifically created to address gender, or ethnicity or age. But the data included variable information for exploratory tests, as under discussion here. One possible theoretical explanation for the difference is that stereotype threat may be mediated by technology, improving pass Completion Rate. However, as can be seen in the data, Gender and Ethnicity seem to be greater indicators of pass or not-pass outcomes than technology does. Moreover, given the possible issue of age-related technology literacy, Age may obfuscate a clear view of the effects of technology if age-related technology literacy plays a role. Hence all of the exploratory results to this point were examined further in a full model.

Full Model Discussion. The Full Model allows for some degree of comparison even if no real conclusions can be drawn. The key finding in Model 1 regarding the effectiveness of a Technology DMC design for improving Completion Rate was the focus of the research, and except for in Model 3, it held true throughout the model tests. Interestingly enough, the statistical significance for Technology DMC design returned in the Full Model when all variables were included together.

Age, Female, Mixed, Black, and American Indian all still indicate statistical significance in the Full Model with Technology DMC also indicating statistical significance while the latter effect was not present when Age was excluded from the modeling. Essentially, every independent variable except for Hispanic and Asian demonstrates statistical significance in the Full Model, with the directional nature of the effect consistent with prior models. Finally, all the variable coefficients worsened their negative effects or reduced their positive effects in the coefficients with the exception of Technology DMC and American Indian. American Indian Ethnicity may be a complicated variable to sort out in its specifics as to why it has such a positive increase. The worsening of all other coefficients while Technology DMC improves in its effect when Age is added again may suggest that Technology DMC benefits are most notable for younger students and that in general some degree of technology literacy effect may be occurring, which may further problematize interpretation of stereotype threat effects.

This research, though, cannot make these claims conclusively. These observations may promote new innovative research in the future.

Again, in short, it might be tentatively stated that Teacher DMC appear to be better for Females and American Indian students and worse for Mixed and Black students. All of the findings beyond Model 1 are of importance mostly in trying to fill a major gap in the research on developmental education mathematics with regard to technology literacy and stereotype threat, even beyond the gap in research on the efficacy of technology on student outcomes in mathematics courses. Interpretation of the R-squared value must be cautious, however, because the dependent variable is a binary or dichotomous variable. A better interpretive statistic for logistic regression can at times be odds ratios, but the R-squared does at least give some sense of change between models.

Limitations of the Study

This study was limited by population data from one community college used as a convenience sample. The study is further limited by the confines of the technology DMC. In other words, different results could be seen should MCC have used alternative instructional or delivery methods in their technology DMC other than ALEKS. However, the data were tested with diagnostics that showed no unexpected or undesired behavior in the data. In terms of generalizability as mentioned in the last section, the generalizability of test results is limited to adult student populations in developmental education, which may be further narrowed to colleges like MCC for future research to develop hypotheses. The findings may be best suited for other Midwest community colleges initially for future research, but the findings may also be of interest in nationwide research because of the unusually diverse nature of MCC compared to other Midwest community colleges. In terms of other disciplines, the literature review in Chapter 2 helps to situate the operationalized variables in the appropriate social science field within education. Most importantly, beyond the efficacy of technology in improving outcomes for students in developmental education mathematics, the other findings serve primarily as potential guidelines and insights for future research.

Recommendations

Recommendations have been listed in a bullet form, and some elucidation follows The first recommendation derives directly from the primary overarching purpose of this study in evaluating the effectiveness of technology DMC in development education. Further research should be encouraged as well, but the findings of this study support the use of technology DMC in developmental education mathematics courses at community colleges. Based on the outcomes of this study, recommendations include the following:

- Advise community colleges to invest more resources in technology DMC, particularly in developmental education mathematics programs, along with further research to build on and corroborate the findings of this study.
- Delve deeper into the theory of stereotype threat through a qualitative study that involves interviewing students and gaining their perspective on their experiences.
- A third recommendation for further study into stereotype threat would be a mixed-methods study from the perspective of the faculty. There may be value in gathering data regarding perceptions through a survey and then comparing that data with statements made through faculty interviews. A combination of

quantitative and qualitative research may lead to a rich discussion of faculty perceptions of underprepared students in the area of developmental mathematics.

- A fourth recommendation would be to replicate this study at the other community colleges across the state, as many of those colleges are including computer-assisted learning in their coursework.
- The study could also be extended to include developmental reading and writing courses.
- The study could be replicated at high school.

Per the initial statement to begin this chapter regarding the promotion of technology-directed learning for developmental education mathematics courses overall, it would be very fruitful for community colleges in the Midwest overall, perhaps even nationwide, to replicate the evaluation of the base efficacy of technology for their programs. If they have not yet initiated technology DMC at their institutions in a significant way or at all, colleges could develop pilot studies to compare their results to the results in this study. Community colleges that have already initiated such programs may be able to do the research in a very time efficient way without needing to expend much in the way of resources in simply conducting statistical tests of population level data in developmental education mathematics programs treated as convenience samples to compare to this study's results, all of which would be even more useful if cohered into a greater collection of data for Midwest community colleges. Amassing such data would prove beneficial across the board for higher education, but especially at the community college level.

This study was focused on developmental education not only because of the availability of the data when MCC switched from teacher DMC to technology DMC in its mathematics programs but also because developmental education at community colleges may be a key point of focus for observing how and why students manage to internalize positive student identities to facilitate their success along their educational trajectories. Students who are attempting to attain degrees or training in post-secondary education and who also must start in developmental education often face stiff barriers to acquisition of successful college identities, as discussed in the literature review and related to Tinto's framework. Therefore, early success academically may be critical to constructing such an identity. The research design, then, may be extended to all developmental education, including reading and writing programs as well in that they too may pose serious challenges for students attempting to transition to post-secondary education but needing the developmental education along the way.

The exploratory aspect of this study indicates that further research should try to tease out whether it truly is stereotype threat or whether the issue may be more complicated in socioeconomic factors that leave some groups underprivileged in basic educational skill sets before they arrive at college.

Implications

This study contributes to making sure that colleges are preparing adults to be ready to enter the workforce with the skills and knowledge they need to be successful. Identifying the most effective course designs for developmental education mathematics learners hastens the rate at which students transition to regular college coursework, thus decreasing the amount of time before they enter the workforce as well as the total resources a college must allocate for each student to proceed successfully along each respective educational pathway. These outcomes can be seen as significant pragmatic outcomes for the community colleges and their student populations overall.

The potential implications for positive social change extend to the potential for developing teacher awareness training programs at MCC and other colleges if human biases seem evident, though such findings go beyond the purview of this research; the recommendations in the prior section included suggestions immediately relevant to elucidating such potential human biases, with the mixed-methods research in the second recommendation being the most immediately relevant. Nonetheless, any research that evaluates the role of technology for students overall in the modern context of a rapidly evolving tech-based society provides important contributions to society overall. Thus, the exploratory research aspect of this study in examining the role of technology in age-related technology literacy begins to tackle a tremendously relevant issue for contemporary and future society. Finally, despite the long-term development of the literature on stereotype threat, much still remains unaddressed in finding solutions to combat stereotype threat. Although this study cannot be conclusive in its exploratory findings, the findings do suggest that future research may find some connection between technology and mediation of stereotype threat.

All of these social implications connect to the overarching theory for this study. Tinto's theoretical framework provides a foundation from which to explore the possible intersections of variables that have been observed historically to be associated with education outcomes: gender and ethnicity. Much research in the past has focused on gender and ethnicity in K-12 education, especially as components of the broader social science category of socioeconomic status. With the rise of nontraditional students, who are often identified by their advanced age when compared to traditional students directly out of high school in beginning or returning to post-secondary education after elimination of their workforce positions and who often are also seeking retraining in the rapid changes in a globalized economy, community colleges fulfill an important role in retraining these workers with skills for the new economy. Thus, this quasi-experimental pilot study can contribute to a better fit between workforce demands and educational services at community colleges, particularly in aiding community colleges in finding the most effective ways to promote efficient, cost-effective retraining for workers in a rapidly changing labor market (Hodara & Xu, 2016; Martinez & Bain, 2013; Super, 2016). This study, thus provides important information for colleges that are making difficult decisions in preparing adults to be ready to enter the workforce with the skills and knowledge they need to be successful. In sum, then, this study helps to build bridges between developing best practices for strong student learning outcomes, efficient use of college resources, and promoting a highly-skilled 21st century workforce.

Conclusion

The purpose of this study was to determine how technology may be beneficial or detrimental to different student populations in a developmental education program shifting from teacher DMC with greater teacher-student interaction to technology DMC at a Midwest community college identified as MCC. The research questions were designed to determine how the student course completion rates compared between teacher DMC and technology DMC with additional exploratory questions including the predictor variables of age, gender, and ethnicity.

The outcomes of this study indicated there is a statistically significant difference in completion rates between technology DMC and teacher DMC at MCC. Overall, students were more successful in technology DMC. Students under the age of 30 performed better in technology DMC, and Native American students performed bettered in teacher DMC than did other ethnic groups. Therefore, the strong take-home message is: per Tinto's framework, students who experience success early in their educational trajectories should integrate into the institutional culture and educational culture overall, reinforcing their sense of belonging within the institution and postsecondary education in general. Further, according to Tinto's theory, students are more likely to persist if they are able to be successful in small, repeated steps, so early success in developmental education is crucial. Through research and study, educators can individualize educational methodology and delivery in the learning mode that is best for the individual learner. As students learn through small successes early in their educational process, whether through technology directed or teacher directed, they integrate into the college culture and are more likely to be retained and complete.

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