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The Remedial Math Process:
Age and Other Factors Affecting Attrition among Students in Community Colleges

A Dissertation

Submitted to the Graduate Faculty of the
University of New Orleans
in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy
in
Education Administration
Higher Education

By

Emily B. Campbell
B.S. Louisiana State University A&M, 2004
M.P.A. Louisiana State University A&M, 2009

December, 2016

Dedication

I dedicate this body of work to my mother, Marcia Bannister, who has been mother,

father, and friend to me. It is she who instilled in me a love of learning and desire to help others.

May I never stop learning and may the things that I learn help me to help others.

Acknowledgement

I would first like to acknowledge my Chair, Dr. Christopher J. Broadhurst, for his guidance and patience with me throughout the development and completion of this study. In addition, I would like thank the other members of my committee, Dr. Brian Beabout, Dr. Ann O'Hanlon, and Dr. Marc Bonis, for their guidance. While a dissertation has only one author, it is not without mentorship. I am thankful to each of these scholars for their mentorship.

I also owe a great deal of gratitude to several employees at the Louisiana Community and Technical College System Office who assisted me in gathering the data needed for this study. First, I would like to thank Dr. Paul Carlsen, who secured permission for me to utilize the data for this study. Secondly, many thanks go to Ms. Amber Gazave, Ms. Sandra Kowalski, and Mr. Paul Monteleone, all of whom assisted me in extracting the data I needed for this study from the Banner database.

Last, I would like to thank my dog, Mardi, who faithfully lay on the floor beside me night after night as I wrote. Writing a dissertation can be a lonely venture, but I was lucky because I had Mardi, my constant companion, by my side throughout.

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Abstract

This study conceptualized remedial education as an attrition process in which students either progress onto the next stage or they do not, and had a particular emphasis on how age affects students' remedial path. The purpose of this quantitative study was twofold. The researcher first sought to understand the points at which students fail to progress within the remedial math process (enrollment in remedial coursework, completion of the remedial sequence, enrollment in a college-level course, and passing the college-level course), and to statistically model the pre- and post-college entry predictors of that attrition among first-time, associate degree-seeking students referred to remedial math in community colleges in Louisiana. The study also had a particular focus upon the effect age has on students' ability to successfully remediate. Longitudinal, student-level data from ten community colleges in Louisiana were used for the analysis. Multiple logistic regression analysis was utilized to answer the research questions.

Results showed the first step in the remedial process (enrolling in a remedial math course) to be the greatest attrition point, with 88.2% of students failing to enroll in a remedial math class. Gender, high school GPA, age, full-time enrollment, and college GPA were found to be significant predictors of remedial math course enrollment. In terms of the second step (enrollment in a college-level math course), age, extent of remedial math need, unmet financial need, high school GPA, and college GPA were found to be significant predictors. By the third step (enrollment in a college-level math course) and fourth step (passing, with a grade of C or better, a college-level math course), the significant covariates narrowed to extent of remedial math need and college GPA, respectively. With regards to age, this study's findings reveal that age matters during the first two stages of remediation (enrollment in a remedial math course

and completion of the remedial math sequence). Specifically, age decreases the likelihood of enrolling in a remedial math course but increases the likelihood of completing the remedial math sequence.

CHAPTER 1: INTRODUCTION

In his first State of the Union address, United States President Barack Obama established, with a single statement, what would become a pillar of his presidency's postsecondary education agenda, stating, "By 2020, America will once again have the highest proportion of college graduates in the world" (Obama, 2009). He continued with a call to action, asking that every American "commit to at least one year or more of higher education or career training" (Obama, 2009). This ambitious goal has since become known nationwide as the College Completion Agenda, and has been supported through funding by several philanthropic groups, including the Lumina Foundation, the Bill & Melinda Gates Foundation, the Carnegie Corporation of New York, the W.K. Kellogg Foundation, the Ford Foundation, the Kresege Foundation, and USA Funds (Russell, 2011; Shapiro, et al., 2015). According to Russell (2011), funding has supported media campaigns to raise awareness among the general public about America's need for more college-educated individuals and lobbying activities to influence public policy. In addition, funding has been utilized through grant monies given to colleges to improve completion outcomes and to fund research by various consultants on best practices for increasing graduation rates (Russell, 2011).

Beyond the political and philanthropically-sponsored rhetoric, nationwide data does indeed reveal a pressing economic need to increase the number of American citizens who enroll in college and subsequently complete a credential. Over the past decade, the number of college-educated workers in the economy has not kept pace with employer demand. According to Carnevale and Rose (2011), the supply of college-educated workers increased 1% per year from 2000 to 2010, while demand for such workers grew, on average, 2% per year. As a result,

Carnevale and Rose (2011) project 20 million more college-educated individuals will need to be added to the economy by 2025 in order to meet workforce demands.

Approximately 57% of Americans aged 25 to 64 have no postsecondary credential –no technical diploma, no associate's or bachelor's degree (U.S. Department of Education, 2014). These individuals represent an untapped market for meeting America's workforce demands. In response, many states have begun focusing upon increasing the number of citizens aged 25 and older who enter, progress through, and ultimately graduate from college (Council for Adult and Experiential Learning, 2008).

Community colleges, with their relatively low tuition and open admission policies, provide a crucial postsecondary access point for many Americans (Cohen & Brawer, 1996). In fall 2013, approximately40% of all undergraduate students, and 50% of all undergraduate adult students (defined as students aged 25 and older), were educated in America's community colleges (U.S. Department of Education, 2013). While community colleges provide an important access point for many students, they often struggle, compared with their four-year counterparts, to graduate students.   According to researchers at the National Student Clearinghouse Research Center, 26% of students who begin their postsecondary career within a community college graduate from that same community college within six years (Shapiro, et al., 2015). In contrast, 48% of students who start at a four-year university graduate from the same four-year university six years later (Shapiro et al, 2015). Because community colleges often serve as a transfer point for many students who aspire to a bachelor's degree, their same-institution graduation rates are understandably lower than those of four-year universities. Still, taking transfer into account, only 38% of students who begin at a community college graduate within six years (with either a certificate, associates or a bachelor's degree) from any community college or four-year

university, compared with 61% of those who begin their collegiate studies at a four-year institution (Shapiro, et al., 2015). Initiatives geared towards increasing retention, progression, and credential completion within community colleges is therefore a vital part of meeting the nation's workforce demands.

For the majority of community college students, remedial education is the gateway to credit-bearing college-level courses, and subsequent college completion (Zachry-Rutschow & Schneider, 2011). Nationally, approximately 52% of community college students are referred to remedial education courses upon entry, compared with 20% of four-year university students (Complete College America, 2012). Remedial education is non-credit coursework (typically in math, reading, or English) below college-level, offered to or required of incoming college students who do not meet minimum levels of academic proficiency as determined by scores on a national standardized exam such as the ACT or SAT. Over the past decade, many states have instituted policies prohibiting remediation at four-year institutions, leading students who are academically underprepared to attend community colleges for their remediation needs (Parker, 2007; Davidson & Petrosko, 2015).

Bailey (2009) asserts that low completion rates among students referred to remedial education is one of the most challenging problems facing community colleges today. National analyses reveal that many students placed into remedial courses upon entry into a community college never complete a credential. Citing data from the Department of Education's National Education Longitudinal Study, Brock (2011) reports that only 28% of those taking remedial courses complete an associate degree or other credential within eight and a half years of enrollment in a community college, compared to 43% of those taking no remedial courses. These

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data have led to remedial education being dubbed higher education's "bridge to nowhere" by Complete College America (2012), a national nonprofit higher education research group.

To better understand the low completion rates among remedial students, many researchers have utilized statewide and national longitudinal data sets to study the impact of remedial education upon various postsecondary outcomes such as retention, transfer, and credit accumulation. The resultant research base paints a complex picture of the impact of remedial education, leaving little consensus on whether or not remediation helps, hinders, or yields null effects (Frye, 2014; Horn et al, 2009). While some researchers have found remediation to have a positive impact upon a student's likelihood of being retained at an institution from semester to semester (Bettinger & Long, 2009; Frye, 2014) others have found it to have no impact (Crisp & Delgado, 2014). With regards to transfer, several researchers have found remediation to have a positive impact on the probability that a student will transfer to a four-year university (Calcagno, 2007; Calcagno & Long, 2008; Bettinger & Long, 2005; Frye, 2014) while others have found a negative effect (Crisp & Delgado, 2014). Some studies have revealed that remedial education has negative (Martorell & McFarlin Jr., 2011) or null (Hodara & Jaggars, 2014) effects upon credit accumulation. Still, other researchers have found remedial education's impact on credit accumulation to be dependent upon the subject of the remedial course, with math remediation producing a positive effect and English remediation yielding null effects (Bettinger & Long, 2005).

Problem Statement

While retention, transfer, and credit accumulation are important outcomes to study (as they all impact credential completion) they are ancillary to much more germane questions. Why do students fail to complete remediation? Can their attrition from certain points within the

remedial process be predicted, and therefore prevented with some type of intervention? Nationally, only 22% of students referred to remediation complete the remedial course to which they are referred and the associated college-level course within two years (Complete College America, 2012). Failing to complete remediation and the associated college-level course prohibits students from progressing in their curriculum, as most curriculums require passage of some type of basic college-level mathematics and English course (Bahr, 2008; 2010a). For this reason, several studies have focused upon the remedial process itself, seeking to examine where within the process students are lost and how that loss can be statistically predicted, and therefore prevented (Bahr, 2009; Bahr, 2010; Bailey et al., 2009; Perry et al., 2010; Bahr, 2012; Frye, 2014). In sum, these studies have found that certain demographics such as race (Bahr, 2010) and gender (Frye, 2015; Bailey et al, 2009), as well as the degree of remediation the student needs (Bahr, 2009; Bailey et al, 2009; Perry et al., 2010; Bahr, 2012) and financial need (Hoyt, 2009; Frye, 2014) play a significant role in whether or not a student will progress successfully through the remedial process. There is little research, however, on another potentially important variable: age.

Age is a research-worthy variable. Adelman (2005) asserts that age, as a demographic variable, "makes an enormous difference in the distribution of virtually any postsecondary outcome or process," and he argues for analyses which "divide the population by age brackets, or in multivariate models, uses age as an independent variable" (p. 144). The lack of research focusing on the effects of age on the remedial education process is surprising given the logical assumption that age is likely a proxy for many other demographic variables such as life experience, financial independence, years since high school graduation, propensity for being responsible for dependents, and the likelihood of full-time employment while enrolled in college,

all of which can have impacts upon enrollment patterns, retention, transfer and graduation (Choy, 2002a). In general, most studies on remedial education have focused upon traditional-age students (students aged 18-24). This is likely because most of the policy work surrounding remedial education has been done in response to a belief that remediation is a failure of the PK-12 continuum and therefore only affects students just out of high school. There are only a few studies (Calcagno et al, 2006; Bailey et al, 2010; Johnson, 2012) which include research on the impact of age on the remedial education process specifically. Calcagno et al. (2006) found that older students were more likely to need remediation as a short-term refresher as opposed to a semester-length, traditional format course (especially in remedial math), and that older students who enroll in remedial classes are less negatively affected than are younger students in terms of their odds of graduation. In a qualitative study of the experiences of remedial education students in community colleges, Johnson (2012) found tension between younger and older students enrolled in the same remedial courses. In her research, she found both groups mutually dissatisfied with the other, each claiming that the other slowed down the learning process and inhibited their learning in the classroom in some way. Johnson (2012) thus asserts "that the dissonance felt between students of different age groups is a serious matter and needs to be addressed" (p. 98). Bailey et al. (2010) found that older students were less likely than their traditional-age counterparts to complete remedial coursework. In sum, these findings reveal that older students may have markedly different needs than do traditional-age students, and therefore experience the remedial education process in different ways. In sum, age seems to matter.

A better understanding of where within the remedial process students are lost and whether or not that loss can be predicted in any statistically reliable way could shed light on why remedial education has become higher education's *bridge to nowhere* (Complete College

America, 2012) and offer solutions for mending that bridge. Also, exploring age as a major explanatory variable in remedial attrition could bring light on a heretofore understudied variable within the remedial education research base. This study attempted to do both.

Purpose of the Study and Research Questions

This study sought to understand the points at which students fail to progress within the remedial math process (enrollment in remedial coursework, completion of the remedial sequence, enrollment in a college-level course, and passing the college-level course), and to statistically model the pre- and post-college entry predictors of that attrition among first-time, associate degree-seeking students referred to remedial math in community colleges in Louisiana. The study also had a particular focus upon the effect age has on students' ability to successfully remediate. Remedial math (as opposed to remedial English) was chosen as the foci of this study because in Louisiana's community colleges, 92% of students referred to remediation are referred to math remediation. This same trend holds at the national level, with math being the subject in which the greatest proportion of students require assistance (Bahr, 2010; Bahr, 2013; Frye, 2014).

Longitudinal, student-level data from ten community colleges in Louisiana was utilized for the analysis. Louisiana is a yet-studied state in the growing number of statewide studies on remedial education. In addition, the outcomes of remedial students in Louisiana's community colleges are more sobering than national statistics, with 63.1% percent of entering students in need of remediation, 47.4% completing remediation, 13.8% completing remediation and the associated college-level course, and only 2.7% graduating with an associate's degree within three years (Complete College America, 2012). The research questions for this study were:

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(1) What are the most significant pre- and post-college entry predictors of remedial math education outcomes (enrollment in a remedial math course following referral, completion of the remedial math sequence, enrollment in a college-level math course, and completion, with a grade of C or better, of a college-level math course)?

(2) Is age a significant predictor of various remedial math education outcomes (enrollment in a remedial math course following referral, completion of the remedial math sequence, enrollment in a college-level math course, and completion, with a grade of C or better, of a college-level math course)?

Theoretical Framework

The central question of this study was an exploration into the predictive factors of remedial education success. This research question is, at its root, a study of remedial education attrition. As Bahr (2009) pointed out, ''remediation is as much a dynamic process as it is an outcome'' (p. 701).Remedial education programs are designed as a pipeline to which underprepared students (often determined by scores on a standardized test) are funneled. Once in the pipeline, the student is expected to learn or re-learn the skills he or she does not possess in order to be ready to enroll in and pass college-level courses (Bailey et al, 2010; Bahr, 2012). By conceptualizing the remedial education process (enrollment in the remedial course to which the student is referred; completion of the remedial education sequence; and enrollment and performance in the associated college-level class) as a process in which students either progress onto the next stage or not, remedial education becomes a retention or attrition pipeline.

Considering this conceptualization, Bean and Metzner's (1985) Nontraditional Undergraduate Student Attrition Model (hereafter referred to as Bean and Metzner's Model) was chosen to serve as the theoretical framework for this study. Bean and Metzner's (1985) Model

provides a context for understanding the specific variables that affect student engagement and retention within the postsecondary education setting. It has been used to study nontraditional students' decision to stay enrolled or drop out of college. The theory defines a nontraditional student as any student who is more than 24 years of age, or is enrolled part-time, or is a commuter student. All community colleges in Louisiana are commuter campuses. Thus, every student in the study (no matter their age) was a commuter and therefore nontraditional, based upon Bean & Metzner's (1985) definition of the nontraditional student.

Bean and Metzner's (1985) Model was chosen because it was developed to specifically study the attrition of nontraditional students. Other attrition models (Tinto, 1975; Pascarella & Chapman, 1983) focus upon traditional-age students, typically enrolled in a residential college setting. The major difference between Bean and Metzner's (1985) Model and other attrition models (Tinto, 1975; Pascarella & Chapman, 1983) is the removal of social integration as a major explanatory variable in students' decision to drop out or stay enrolled in college. While Stahl and Pavel's (1992) Community College Retention Model also focuses less on social integration, Bean and Metzner's (1985) Model was chosen instead due to its ability to span institutional type. While this focused upon students within community colleges, the use of Bean and Metzner's (1985) Model, which was designed to span institutional type, allows the study to be replicated for future research with nontraditional students within any type of institutional setting.

Methods

Many college outcomes are dichotomous in nature. Students are either retained from one semester to the next, or they are not. They graduate, or they do not. Higher education researchers who wish to understand the factors influencing dichotomous outcomes have at their disposal

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several statistical techniques, including: discriminate analysis (Marascuilo & Levin, 1983), log-linear analysis (Christensen, 1990), and logistic regression (Hanusheck and Jackson, 1977). Because all four outcome variables in the study were dichotomous and because there were multiple independent variables the researcher utilized multiple logistic regression analysis to address each of the research questions. Logistic regression has been used in higher education research since the 1970's (Cabrera, 1994) to study college enrollment decisions (Bishop, 1977; St. John & Noell, 1989) and persistence (Stage, 1988).

Significance

The nation's current economic need to drastically increase the number of citizen's with a college credential has produced a growing mandate to address the dismal outcomes for students referred to remedial education in America's community colleges. Remediation represents a bridge to nowhere for thousands of students nationwide, with only 22% completing remediation and the associated college-level course (Complete College America, 2012). Several studies, utilizing nationwide or statewide data, have provided some information on the major factors that influence whether or not a student will progress successfully through the remedial process. These studies have revealed that the extent of remediation a student needs (Bahr, 2009; Bailey et al, 2010; Perry et al., 2010; Bahr, 2012) as well as race (Bahr, 2010) play a major role. These studies have focused mostly upon traditional-age students (aged 18-24). Considering its covariance with other demographic variables such as financial independence, propensity for being responsible for dependents, and the likelihood of full-time employment while enrolled in college(Choy, 2002a; Adelman, 2005), age is likely a research-worthy variable within the remedial education research base. This study explored the major attrition points within the remedial process, statistically modeled the pre- and post-college entry predictors of that attrition,

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and sought to understand the influence age has upon various remedial education outcomes. The findings from this study have scholarly, practical, and policy-oriented implications.

From a scholarly standpoint, the application of Bean and Metzner's (1985) Nontraditional Undergraduate Student Attrition Model to the study of remedial education attrition is novel. In addition, this study expanded the model with an additional variable specific to the study of remedial education. Findings also confirmed age as a research-worthy variable within the remedial education research base. This is important considering that adult students make up 43% of the remedial population in community colleges nationwide (Complete College America, 2012). Considering the nation's economic need for practices which increase the number of citizens who enter, progress through, and ultimately graduate from college, research that provides insights into any differential impact of any form of postsecondary education delivery (remedial education included) on demographic groups that make up a large percentage of the student population is warranted.

From a policy and practice standpoint, this study offers findings on which student-level variables matter and when they matter specifically within the remedial process. High attrition rates among remedial students represent a significant opportunity cost for colleges. Absent a clear understanding of where within the remedial sequence students are most likely to abandon the remedial process, practitioners have little guidance on when to offer proactive interventions. Knowing that certain students, based upon their background or demographics, have an increased risk of leaving the remedial process at a certain juncture, practitioners can more strategically target certain interventions to certain students at certain points. For example, findings from this study reveal that the greatest attrition point for remedial math students in Louisiana is at the first step within the remedial process (enrolling in a remedial math course following referral).

Specifically, this study found that older students, students enrolled on a full-time basis, female students, and students with higher high school GPA's were less likely to take that first step.

This study's findings also have implications for PK16 policy and practice. The need for remediation signifies some degree of misalignment between the secondary and postsecondary system. Findings from this study reveal that a students' ACT math sub-score is a predictive factor in whether or not a student will successfully navigate the remedial math sequence and subsequently enroll in a college-level math course. Calculating the odds based upon ACT sub-score, this study gives statistical precision to the possible development of an early alert system and interventions within the K12 system.

Some policy makers contend that remediation has little value and have called for its elimination altogether (Fain, 2013). Many researchers, on the other hand, continue to assert that remediation plays a vital role in promoting access to postsecondary education (Mellow & Heelan, 2008; Bahr, 2010; Howell, 2011). Because minority, first generation, and low socio-economic status students are disproportionally represented in remedial courses (Complete College America, 2012; Bahr 2010), remediation represent a gateway to postsecondary education for historically underserved populations. Howell (2011) contends that despite low retention and graduation rates among remedial students, those who are successfully remediated have similar outcomes to those who started college with no remedial need. In other words, when remediation works, it works. This study did not seek to enter the debate about whether or not remedial education is valuable. It instead started from the premise that remediation plays a vital role in promoting access to postsecondary education. From this premise, this study sought to better understand the bridge to nowhere in an effort to provide insights not for its dissolution, but for its repair.

Definition of Terms

Adult Students. Students aged 25 and older.

Credential. Any undergraduate postsecondary award, including technical certificates, diplomas, associate's degrees, or bachelor's degrees.

Nontraditional student. Any student who is more than 24 years of age, or is enrolled part-time, or is a commuter student.

Remedial course sequence. Multiple remedial courses which are designed to be taken successively.

Remedial education. A process in which academic weakness is detected through assessment, and instruction is provided to remove a student's deficiencies in order to bring him/her to a prescribed level of proficiency (Rubin, 1991).

Remediation level. The point within the remedial course sequence to which the student is referred.

Traditional-age student. Students aged 18-24.

CHAPTER 2: LITERATURE REVIEW

This study, conceptualizing remediation as an attrition process, focused upon age and other factors that affect attrition from the remedial math process among students in the community college setting. The literature base informing this study was varied and consisted of literature on the history of remedial education in American postsecondary education, contemporary issues surrounding remedial education, community colleges and their role within the wider postsecondary education context, adult learners and adult learning theory, research on the impact of remedial education on various postsecondary outcomes, and the development of attrition models for nontraditional undergraduate students. All of these strands of literature informed this study as they, in the aggregate, formed a conceptual framework in which the study was developed and implemented.

Remedial Education

Providing services to the academically underprepared has been a function of American higher education since the academy's inception (Arendale, 2002b). While the terminology to describe these services has changed throughout the years, the core function of assisting students who come to college in some way un- or underprepared for the rigors of college life and coursework, has remained the same. Understanding the historical development of remedial education can shed light on its current form and the contemporary controversies surrounding it. Therefore, in this section, a brief history of remedial education is provided, followed by a description of its current form within most postsecondary institutions throughout the United States. Lastly, a discussion of some of the contemporary challenges and issues facing remedial education is provided.

Historical Perspectives

The act of providing services to underprepared students began in the 1600's with the founding of America's first universities, Harvard, Yale, and William and Mary (Arendale, 2010). Throughout history, these services have been called many things, including *preparatory*, *remedial*, *compensatory*, *developmental*, and *enrichment* (Arendale, 2010). Today, according to Arendale (2010), "…institutions across the United States employ more than 150 titles for the centers and departments that provide these services" (p. 4). The term *remedial education,* which will be used to describe these services throughout this study, was developed following the American Civil War and has been used to describe a process in which academic weakness is detected through assessment, and instruction is provided to remove a student's deficiencies in order to bring him/her to a prescribed level of proficiency (Rubin, 1991; Lewis & Farris, 1996).This study utilizes the term *remedial education* as a way to denote that the study's main focus is upon the remediation process (referral to remedial classes based upon assessment, the taking of remedial courses to remedy academic deficiencies, and the completion of the college-level course as an indication of achievement of a prescribed level of proficiency).

Remediation has roots in the founding of the American academy. From the 1600's through the 1800's, poor and noncompulsory secondary schooling, coupled with admission requirements in Latin, Greek, and mathematics, meant that many first-year students were woefully underprepared for the rigors of collegiate coursework. Harvard University required remedial studies, in the form of tutoring, for most of its freshman class throughout the 1700's through the first half of the 1900's (Boylan & White, 1987). Tutoring often consisted of recitation sessions in which tutors read aloud lesson materials to students who were expected to recite back, verbatim, the lessons (Arendale, 2010). Since most college students during this early

period were white males from privileged families, Arendale (2010) argues "little stigma was attached, as it was perceived as a natural part of the education process…" (p. 27).

By the mid-1800's, the American education system had expanded to offer more opportunities for the middle class. During the presidency of Andrew Jackson, public education at the elementary, secondary and postsecondary levels was expanded. However, the quality of elementary and secondary education was uneven throughout the United States, and as a result, many students remained underprepared for the rigors of college coursework. Because elite institutions refused to extend admission to underprepared individuals from the ranks of the middle class, and because less selective colleges were unwilling to take on the burden of basic education, preparatory academies were formed (Arendale, 2010). Academic preparatory academies were entities external to the college that served as a sort of bridge into college admission. By the late 1800's almost 40% of college students had gone through some sort of preparatory academy prior to college admission (Ignash, 1997). While the preparatory academies provided an avenue for middle class students to access postsecondary education, they were still external to the college. Postsecondary institutions had yet to institutionalize the process of assisting underprepared students.

The first college to establish an in-house department for assisting underprepared students, beyond the tutoring provided to wealthy students at elite institutions, was the University of Wisconsin, in 1849 (Arendale, 2010). The Wisconsin Model, as it became known, consisted of an academic department, called the Department of Preparatory Studies, which offered courses to admitted students in basic reading, writing, and mathematics (Brubacher & Rudy, 1976).

According to Arendale (2010):

 "Offering remedial courses and other learning assistance services in a college department

addressed many of the problems experienced by external academic preparatory

academies such as lack of coordinated curriculum, poor teaching facilities, lack of proper

administrative control, and increased stigma for participating students" (p. 31).

While the Department of Preparatory Studies at Wisconsin closed in 1880 due to internal critics

who worried about its role in lowering academic standards, other institutions across the United

States implemented similar models throughout the latter part of the 1800's. The First Morrill Act

of 1862 greatly expanded the number of public postsecondary institutions throughout the United

States, increasing access to postsecondary education for more students of modest means. With

this came an increase in remedial course offerings (Arendale, 2010). By the end of the nineteenth

century, roughly 80% of all postsecondary institutions had preparatory departments (Canfield,

1997).

In addition to the rise of remediation within America's less-selective institutions,

remediation remained a key component of even the most elite colleges in the country through the

mid twentieth century. In 1907, half of first-year students at Harvard, Yale, Princeton, and

Columbia failed to earn the required entrance exam score and were enrolled in remedial courses

(Brubacher & Rudy, 1976). At Harvard, the previous recitation tutorial programs were expanded

into courses in the early 1900's (Arendale, 2010). Harvard was the first postsecondary

institution in the country to offer elective courses, allowing underprepared students the flexibility

to take remedial courses in reading, writing, mathematics, and study skills for credit (Arendale,

2010).

In the early 1900's, the funding of public postsecondary institutions began to shift. New infusions of state and federal dollars began to subsidize tuition dollars. In response, many institutions became more selective, admitting less, but more academically prepared students (Richardson, Martens, & Fisk, 1981). Junior colleges (which would later be called community colleges) formed and flourished as a result. The mission of these colleges was broad, but among their varied focus was academic preparation for transfer to more selective universities. Many four-year universities began to refer underprepared students to the local junior college for remediation (Arendale, 2010).

Throughout the mid-1900's several significant events occurred which drastically increased access to, and the federal government's involvement in, public postsecondary education, including the GI Bill, and the expansion of civil and women's rights. As enrollments broadened along socioeconomic, racial and gender lines, so did the stigma attached to remedial education. According to Arendale (2010), "entering students from privileged backgrounds were better prepared academically than the new first-generation college, and economically disadvantaged, students who were entering postsecondary education for the first time" (p. 34). Economically disadvantaged students and students of color had uneven access to quality secondary education and were therefore at greater risk of needing remediation. As a result, "stigma began to attach to the students who enrolled in remedial courses" (Arendale, 2010, p. 34).

In the latter half of the twentieth-century, the role of remedial education was greatly expanded. On the heels of the Civil Rights Act of 1964 and President Lyndon Johnson's ambitious domestic programs, came the establishment of the Office of Compensatory Education within the U.S. Office of Education. The Office of Compensatory Education's mission was to

revamp, re-image and broaden the role of remedial education. Compensatory education was

designed to move beyond simply remediating students academically. In addition to traditional

forms of academic remediation, such as tutoring and remedial coursework, compensatory

education programs included "a new package of activities including educational enrichment and

cultural experiences" (Arendale, 2010, p. 37). New programs, such as TRIO, were established

and would eventually become official entitlement programs (Arendale, 2010).

From the 1970's to the mid-1990's the services offered to underprepared students were

expanded to include various forms of non-credit activities and approaches (Arendale, 2010). On

many campuses this was manifested in the founding of learning assistance centers (LACs).

According to White and Schnuth (1990), LACs were comprehensive in nature, as they provided

a bevy of services (from tutoring to cultural enrichment experiences to study skills assistance) to

all students on campus. "No stigma was attached to LACs" because their services were offered to

all students and because the centers rarely used the term *remedial* to describe any of their

services (Arendale, 2010, p. 43). In addition to LACs, some colleges began re-branding their

remediation services into what would become known as *developmental education*.

Developmental education focused upon the development of the academic and affective domains

(Higbee, 2005; Kozeracki, 2002). In contrast to remedial education, which begins from the

notion of identifying and correcting deficiency, developmental education begins from the notion

of identifying and enhancing talent. Cross (1976) describes the differences between remedial and

developmental education as such:

"If the purpose of the program is to overcome academic deficiencies, I would term the program remedial… If however, the purpose of the program is to develop the diverse talents of students, whether academic or not, I would term the program developmental" (p. 31).

Amid federal and state budget reductions in the 1980's and 1990's, many public postsecondary institutions began outsourcing bookstores, janitorial services, housing, and food services. Several colleges also outsourced the delivery of remedial and developmental courses. The contracts with proprietary entities such as Kaplan and Sylvan Learning Systems were short-lived as they failed to improve student achievement enough to justify the annual contract costs (Arendale, 2010).

In sum, remediation has been a part of the American postsecondary landscape since the academy's founding. Society's perception of it has, however, changed dramatically. As remedial students became less white and more economically disadvantaged, remedial education became increasingly stigmatized. The terminology used to describe it has also changed throughout time, with variations including *compensatory* and *developmental.* Despite terminology changes, the act of providing services to the academically underprepared continues today.

The Modern Remediation Process

From grueling recitation sessions in the halls of Harvard to state-of-the-art learning assistance centers, remediation has been and continues to be a part of American postsecondary education. Modern remediation at most postsecondary institutions consists of a process of testing, placement in remedial courses, remedial coursework (which can include multiple courses), and eventual enrollment in college-level coursework. Students are considered *remediated* if and when they complete the college-level class, oftentimes referred to by

researchers as *gatekeeper courses* (Roska et al, 2009; Bailey et al, 2010; Bahr, 2010). While the overall process is fairly consistent across institutions, the policies governing each phase of the process vary, leading to an inconsistent patchwork of requirements across postsecondary institutions (Bailey et al., 2010; Frye, 2014).

In most colleges and universities today, students are placed (mandated to take) remedial coursework based upon their scores, often referred to as *cut scores,* on a standardized test. The most common tests used for placement are the Accuplacer, a product of the College Board, and the Compass, a product of ACT (Hughes & Scott-Clayton, 2011). Although some states have standardized cut scores across institutions, for the most part, cut scores vary by institution (Hughes & Scott-Clayton, 2011). This lack of consistency makes the need for remediation a relative concept, across institutions and across states. The validity of the tests themselves has also been scrutinized. A growing body of research suggests that such tests "are only weakly predictive of students' success in college-level coursework" (Hodara & Smith-Jaggars, 2014, p. 249). Some researchers have concluded that, as a result, many students are over-placed in remedial courses (Scott-Clayton, Crosta, & Belfield, 2012). Furthermore, several studies have revealed that the testing process itself may lead to a disproportionate number of students being placed into remedial courses. Venezia, et al (2010) found that students in California community colleges were not informed prior to orientation or the first day of class that they would be tested, nor were they informed of the implications of their score prior to taking the placement test. Johnson (2012), in a qualitative study at a community college in Washington, D.C., found that "students were unclear about the purpose of the test, were unprepared to do well on the test, and generally rushed through the test" (p. 77).

The placement process has also been scrutinized. In a national study, Bailey, et al. (2010) found that approximately 30% of students who were referred to remediation did not enroll in any courses – remedial or college-level- during a three-year period following referral. In other words, 30% of students who were referred to remediation simply did not pursue a college credential. Unfortunately, Bailey, et al. (2010) did not compare this rate to students not referred to remedial courses, making it difficult to conclude that it was referral which caused the premature departure. Grubb and Coxx (2005) hypothesized that low remedial enrollment rates may be due to the fact that remedial course credit does not typically count towards a degree, making the value of remedial courses unclear to students.

The coursework in which students are placed may also vary by breadth and depth. Students may be found to have remedial need in more than one subject (such as math, reading, or English). They may also be referred to multiple remedial courses (called a *remedial course sequence)* in any particular subject. The point within the sequence to which the student is referred is often called the *remediation level.* Institutions vary with regards to the levels of remediation offered. Some colleges may offer one level of remediation in any given subject while others may offer up to four (Frye, 2014). Many researchers agree that the lower a student places in the remedial course sequence (the lower their remediation level) the less likely they are to complete the remediation process (Bailey et al., 2010; Jaggars & Hodara, 2011; Jenkins, Jaggars, Roksa, Zeidenberg, & Cho, 2009). Bailey et al. (2010) found this to be true even of students who were passing their remedial courses- they simply failed to show up for the next class in the sequence the following semester. Hodara and Smith-Jaggars (2014) hypothesized that "long sequence lengths and multiple exit points provide too many opportunities for students to leave college prior to completing their developmental requirements" (p. 249).

Contemporary Context

Remediation is perhaps one of the most discussed topics in higher education today. According to Levin and Calcagno (2008), "the 'remediation crisis' has surely become one of the most controversial issues in higher education in recent times" (p. 181). Toracco (2014) advocates for increased scholar-practitioner collaboration in an effort to improve remedial education outcomes, stating that "academic researchers do not have a monopoly on the knowledge to address this problem" (p. 1201). At the heart of the perceived crisis are issues of PK-16 misalignment, cost, and access. While this study did not directly address any of these issues, understanding the context in which remedial education currently resides can provide a framework for understanding this study's findings, and for discerning their possible policy implications.

Pk-16 misalignment. Remediation is not a higher education issue alone. Its existence signifies some degree of misalignment between the secondary and postsecondary system (Byrd & MacDonald, 2005; Conley, 2007), leading many policy makers to feel as though tax dollars are paying for the same education twice (Merisotis & Phipps, 2000). Howell (2011) discusses the complexity of this issue, stating, "by the time students reach college, their ability to handle college-level coursework is based not only on their academic ability and effort, but on a cumulative set of influences from family, teachers, peers, and schools" (p. 292). While policy makers have little direct control over family and peer influences, research that informs teacher and school reform efforts hold promise for increasing students' college readiness.

With regard to teacher characteristics, Howell (2011), in a statewide study in California, found high school teacher quality (measured by level of highest credential attained and years of experience) to be a statistically significant predictor of whether or not high school students

would need remediation once they reached postsecondary education. She however tempered this finding by contending that her study was unable to control for other teacher attributes (work ethic, talent, etc.) that may be just as important to students' college readiness. She in turn called for more research on "classroom activities unique to experienced, fully-credentialed teachers with master's degrees" (Howell, 2011, p. 315).

In a review of the literature on school reform efforts in several states, Martinez and Klopott (2005) concluded that a "combination of a student's academic background, coursework, class rank, and senior year test scores has a stronger relationship to college completion than does socioeconomic status" (p. 5). With regards to academic background and coursework, taking and completing high-level math courses (beyond Algebra) while in high school seems to be the greatest predictor of college success, regardless of socioeconomic or racial/ethnic status (Adelman, 1999; Checkley, 2001; Tierney, Colyar & Corwin, 2003). Other scholars have found dual-enrollment programs (in which high school students take college-level courses taught by a college faculty member) to be effective at creating lines of communication and fostering expectations between secondary and postsecondary institutions (Bailey, Hughes, & Karp, 2003; Venezia, et al., 2005).

Cost. Remediation is estimated to be a very costly endeavor for institutions and for students (Alliance for Excellent Education, 2011; Complete College America, 2012; Pretlow &Wathington, 2011). National estimates put the cost of remedial education, to students and institutions, between two and three billion dollars, annually (Strong American Schools, 2008; Complete College America, 2012).These costs, in combination with the low success rates for remedial students, concern policy makers. Troubled by the cost of remediation and low student success, in 2013, policy makers in Florida made remediation voluntary and exempted recent high

school students from required placement exams in hopes that it would accelerate credential completion (Fain, 2013). While researchers are still studying the effect of this statewide policy shift, preliminary results are troubling, as pass rates in college-level, gateway classes have decreased (Smith, 2015).

For students, remedial education can have financial, opportunity, and psychological costs. Placement into remedial courses means that students have to take additional courses and pay extra money to obtain their college degrees. At some institutions, students placing into the lowest levels of a remedial course sequence in three subject areas would have to complete seven or eight courses, or twenty-one to twenty-four hours of credit, before being eligible to take their first college-level credit course (Scott-Clayton & Rodriguez, 2012). This can substantially increase the financial and opportunity cost of a college education, as students pay for more coursework and forego earnings (Crisp & Delgado, 2014). It is estimated that the average community college student pays close to two-thousand dollars for remediation (Strong American Schools, 2008). Beyond the financial and opportunity cost, remediation may also have psychological costs for students. Some researchers have found placement into remedial courses to have a negative effect on students' academic aspirations (Clark, 1960; Attewell et al, 2006; Venezia, Bracco, & Nodine, 2010; Scott-Clayton & Rodriguez, 2012).

For institutions, the high attrition rate of remedial education students is problematic, especially considering that public institutions spend an estimated $1 billion dollars a year providing remedial services (Bettinger & Long, 2009). According to Bailey et al. (2010), approximately 30% of students who are referred to remediation never enroll in any coursework. Among those that do enroll in coursework, less than half complete the remedial sequence

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(Bailey, et al., 2010). These high attrition rates mean lower retention and graduation rates for institutions.

       Access. Despite the monetary and potential psychological costs, Mellow and Heelan (2008) assert that remedial education is the "centerpiece of the dream of opening higher education to all Americans regardless of prior educational opportunity or success" (p. 165). Bahr (2010) concurs, stating that "remedial coursework represents a lifeline in the ascent to financial and social-structural stability for individuals who face significant deficiencies in foundational subjects" (p. 209). National data reveal that remedial programs do indeed serve a disproportionate share of low-income and minority students- populations that have historically been underrepresented in postsecondary education (Complete College America, 2012). While opponents assert that low retention and graduation rates among remedial students signify that remediation does not work, some researchers argue otherwise. Howell (2011) states, "Remedial college courses may catch those minority students that would otherwise leak out of the system," pointing out that other researchers have found that "remediated students experience increases in college persistence and four-year degree completion" (p. 296).

Community Colleges and Remedial Education

       Nowhere in the postsecondary landscape is the mission of access more acute than within community colleges, which were designed as open-admission institutions. While remediation exists within all types of institutions, it is most prevalent within community colleges (Zachry-Rutschow & Sneider, 2011; Adelman, 2004; Jenkins, Jaggars &Roska, 2009; Bailey, Jeong, & Cho, 2010; Davidson & Petrosko, 2015). The prevalence of remediation within community colleges is logical given the institutions' historic open-admission policies (Boylan & Saxon, 1999) and recent increases in state policies prohibiting remediation at four-year institutions

(Parker, 2007). Reasserting the need for remediation and community colleges' dedication to it at the turn of the twenty-first century, the American Association of Community Colleges stated, "Remedial education represents a key part of the access puzzle and must be an important activity of any community college. It must remain so long as the need for it exists" (American Association of Community Colleges, 2000, p. 19). Yet national data are troubling, revealing that less than 25% of the students who are referred to remedial education in America's community colleges complete the remedial course and associated college-level course (Complete College America, 2012). Taking this into account, are America's community colleges fulfilling their noble remedial education mission?

This study focused on remedial education outcomes across ten community colleges in Louisiana. An understanding of community colleges and their place within the wider postsecondary landscape was therefore important to this study's conceptualization. Therefore, a discussion of the role, scope and mission of community colleges, and the students they serve follows. The section concludes with information on remedial education within Louisiana's community colleges.

Community Colleges' Role, Scope, Mission and Student Body

Community colleges are an American invention and, as noted by Mellow and Heelan (2008), were "created to revolutionize college education in the United States" (p. 1). Today, there are approximately 1,100 community colleges in the United States, with an enrollment of 7.3 million, credit and noncredit, students (American Association of Community Colleges, 2016). In fall 2013, half of all undergraduate students were educated in America's community colleges (U.S. Department of Education, 2013). During the 2013-2014 academic year,

America's community colleges awarded approximately 795,000 associates degrees and 495,000 certificates (American Association of Community Colleges, 2016).

Community colleges serve various, and often conflicting, missions (Hodara & Jaggars, 2014). Reflecting upon community colleges' history and future, Dougherty (1994) dubbed them "the contradictory colleges." From transfer to short-term workforce training, to remediation to associate degrees, community colleges serve students with a wide range of aspirations (Johnson, 2012).Community colleges are vital to meeting America's future workforce needs. As Cohen and Brawer (2009) point out, community colleges can produce associate degree holders in two years as well as a variety of shorter term, but meaningful, work credentials in a year or less. Furthermore, community colleges are able to respond to local needs more quickly than are four-year universities (Cohen & Brawer, 2009).

Because of their diverse missions, researchers have developed various definitions of community college student success, with most studies focusing upon retention, persistence, and completion or transfer to a four-year institution (Frye, 2014).Community colleges often struggle to improve student success measures such as retention and graduation, in part, due to their limited financial resources, relative to their four-year brethren (Mullin & Honeyman, 2007; Mullin, 2010).

Community colleges enroll a large percentage of non-traditional students (CCSSE, 2005). Non-traditional students are defined as students who: delay enrollment into postsecondary education; attend college part-time; maintain a full-time job while attending college; are financially independent for financial aid purposes; have dependents other than a spouse; or, are single parents (U.S. Department of Education, 2015). Approximately 17% of community college students are single parents, 62% attend part-time, and 38% are employed full-time while

attending college (American Association of Community Colleges, 2016).   In addition,

approximately 36% of community college students are the first in their family to attend college

(American Association for Community Colleges, 2016).

Adult Students and Adult Learning Theory

The average age of community college students is 28, and as stated above, 50% of all

undergraduate adult students are educated in America's community colleges (U.S. Department of

Education, 2013). Adult students represent a growing segment of higher education enrollment.

According to the U.S. Department of Education (2015), over the past decade, adult student

enrollment has increased at the same rate (35%) as traditional-age student enrollment. The rate

of increase for adult students is projected to surpass that of traditional-age students through 2023,

with adult student enrollment projected to increase 20% and traditional-age enrollment projected

to increase 12% (U.S. Department of Education, 2015).

Adult students are considered a subset of nontraditional students in the educational

research literature. Horn and Carroll (1996) developed a ranking scale to rank students from

minimally nontraditional to highly nontraditional. Utilizing Horn's ranking scale Lane (2004)

found many adult students ranked as highly nontraditional, putting them at substantial risk for

not completing a degree. According to Shapiro, et al. (2015), approximately 61% of adult

students nationwide who began seeking a degree in 2009 had not obtained a degree six years

later. Considering these statistics, Cox and Ebbers (2010) state succinctly, "The time has come

for a more thorough examination of the postsecondary educational experiences of adult

learners…" (p. 339). In a phenomenological study of adult female students attending a

community college in the Midwest, Cox and Ebbers (2010) found that the decision to persist

among the study participants was heavily influenced by the support of family and friends,

learning to juggle multiple roles and emotional challenges, and the presence of supportive teachers and a diverse student body.

There is a growing body of literature positing that adult students have markedly different needs than do traditional-age college students (Ashar & Skenes, 1993; Naretto, 1995; Braxton & Brier, 1989; Benshoff, 1991; Donaldson & Graham, 1999). The Council for Adult and Experiential Learning (2005) asserts that adult students need: institutional flexibility in curricular and support services; academic and motivational advising supportive of their life and career goals; and recognition of previously obtained experience- and work-based learning. Perhaps the most seminal piece of research on the different needs of adult students is that of educator Malcolm Knowles. Knowles (1980) contrasts the way adults learn (andragogy) with the way children learn (pedagogy), asserting that adults can and should direct their own learning, can draw upon life experiences to aid in learning, are problem-centered and therefore learn best when applying learning immediately to real-world situations, and are often more motivated to learn by internal rather than external factors. These findings have implications for practice and Knowles (1984) suggests that adult educators: explain and demonstrate why a specific skill or piece of knowledge is important to learn; focus upon tasks as opposed to rote memorization of facts; and involve learners in the solving of real-world problems.

Knowles' (1984) theory has direct implications for practitioners engaged in designing and delivering remedial education to adult students. Kenner and Weinerman (2011) assert that "developmental educators must understand the background of adult students and develop a curriculum that addresses their particular needs" (p. 90). They argue that adult learners often come or return to college with learning strategies they developed within their work life, many of which are "not conducive to collegiate learning, and in some cases, may be detrimental" (Kenner

&Weinerman, 2011, p. 93). For example, the skills one employs in learning how to do repetitive tasks in the workplace are different than the skills one needs to use to creatively dissect and interpret a work of fiction or a sonnet. Kenner and Weinerman (2011) therefore advise remedial education instructors to "frame learning strategies in a way that allows adult learners to see the purpose of the exercises," engage the adult learner in the comparison of the old and new strategy, and provide the adult learner with enough varied opportunities to test the usefulness of the strategy (p. 94).

Unfortunately, many remedial education courses are designed to mimic the secondary classroom. In a study of remedial courses in California community colleges, Grubb (2013) found that the majority of remedial instructors used an approach he called "remedial pedagogy" (2013, p. 52). According to Grubb (2013), this approach emphasized drill and practice, the teaching of de-contextualized sub-skills, and the use of lecture and demonstration; all done in an instructor-centered classroom absent student involvement or active learning. When describing the remedial classrooms he observed, Grubb (2010) laments that there was:

> "an emphasis on getting the right answer, rather than on any conceptual understanding of why an answer is correct, or how to develop alternative 'right' approaches to solving a math problem, writing an essay, or interpreting a reading passage" (p. 12).

He goes on to say that "very seldom is instruction contextualized," as he observed "no reference to how basic reading or writing or math might be used outside the classroom, either in subsequent classes or in the world outside schooling" (p. 12). Hamilton (2012) argues for contextualized learning in the remediation classroom, stating that "students need to see themselves learning a marketable skill" (p. 1017). He does contend that contextualization is

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difficult, although not impossible, to implement as it often requires major structural changes to the curriculum and comprehensive training for faculty (Hamilton, 2012). However, studies of remedial education contextualization have shown positive results (Bloom & Sommo, 2005; Jenkins et al, 2009). While this study did not address nor statistically account for teaching practices in remedial education classrooms, understanding that inappropriate teaching practices may play a role in adult student attrition from the remedial education process is important to understanding the broader context of this study and its findings.

The Louisiana Context

The setting for this study was community colleges in Louisiana. Understanding the State's current remedial education policy framework and the evolution of that framework was therefore important. Overall, the evolution of remedial education policy in Louisiana has taken place as part of a series of statewide minimum admission policies which have sought to channel an increasing number of students, especially those with remedial need, from four-year universities to Louisiana's community and technical college system. Most of Louisiana's public post-secondary institutions were founded in the latter half of the nineteenth century. Until the early years of the twenty-first century, most were open-admission and most offered an array of degrees, from the associates through the doctorate, and no statewide policy on what constituted remedial need existed (Manning, 2006). In 1999, the Louisiana Community and Technical College System (LCTCS) was founded (LCTCS Act, 1998a; LCTCS Act, 1998b) and a slow policy push began to move all degree programs below the baccalaureate level to LCTCS institutions, and to divert students with remedial need away from four-year institutions to community colleges (Remedial Education Commission, 2011).

In 2001, the Louisiana Board of Regents, the State's public postsecondary coordinating board, established a statewide minimum admissions criteria framework and policy (Louisiana Board of Regents, 2011) for all four-year (non-LCTCS) institutions, with implementation to begin fall 2005. The admissions criteria framework and policy organized Louisiana's four-year institutions into tiers (flagship, statewide and regional); articulated what constitutes remedial need; and dictated minimum academic requirements (ACT composite scores, high school curriculum, high school GPA) for admission to each of the three tiers of four-year schools. In order to enroll in college-level math, students must have at least a 19 on the math sub-section of the ACT or at least a 40 on the Algebra COMPASS exam. To enroll in college-level English, students must have at least an 18 on the English sub-section of the ACT or at least a 70 on the Writing Skills COMPASS exam. In addition, students with any remedial need were no longer eligible for regular admittance to the flagship institution. Students regularly admitted to statewide or regional institutions could have remedial need in no more than one subject area. Institutions could however admit students by exception, with the number of exceptions exceeding no more than 15% of the total entering class. In 2006, the allowable exceptions were revised to 5% at the flagship institution, 7% at statewide institutions, and 10% at regional institutions.

In 2010 the Louisiana legislature passed Act 741, also referred to as the LA Grad Act (Louisiana Grad Act, 2010), which stated that beginning in fall 2016 no remedial courses would be offered at any four-year university in Louisiana. Promulgated by the LA Grad Act, the Louisiana Board of Regents in 2010 revised its Statewide Minimum Admissions Policy, stating that students needing remedial education would not be eligible for regular admission to any statewide institution (except by exception) beginning fall 2012 and to any regional school

(except by exception) as of fall 2014. This, in effect, relegated all remedial coursework to Louisiana's two-year intuitions.

Research on the Impact of Remedial Education on Various Postsecondary Outcomes

Researchers have been studying remedial education for more than three decades (Levin & Calcagno, 2008).Unfortunately, many studies have utilized weak methodological practices or failed to adequately account for potential selection bias (Bettinger & Long, 2005; Moss &Yeaton, 2006; Crisp & Delgado, 2014), limiting their reliability and use for practice. As Bettinger and Long (2005) state, "Better-prepared students are less likely to be placed in remediation and they also do better in college…thus, simply comparing remedial students with non-remedial students is an unsatisfactory way to establish the true effects of remediation" (p. 23). Studies which have failed to account for selection bias, according to Crisp and Delgado (2014), could be to blame for some previous findings which assert that remedial education has a negative impact upon student outcomes. They point to studies by Bettinger and Long (2005) and Attewell et al (2006) which, after properly controlling for student background, found remedial education to have no negative impact upon student outcomes (Crisp & Delgado, 2014). Of those studies which have employed sound methodological techniques, the results have been mixed (Horn et al, 2009), or have focused upon single institutions, limiting their generalizability (Frye, 2014). In summing up the research to-date, Crisp and Delgado (2014) conclude that "little is known about the causal effects of developmental education for students who enroll in remedial courses at the community college level" (p. 3). Yet "given the potential importance of such courses to the trajectories of students toward outcomes of policy interest (i.e., graduation)…application of designs and analytic strategies that allow for such causal conclusions is paramount" (Horn et al, 2009, p. 514).

The following section will highlight contemporary studies which utilized statewide or national longitudinal data sets to study the impact of remedial education on a variety of postsecondary outcomes, including retention/persistence and transfer; credit accumulation; enrollment/performance in gatekeeper courses; and degree completion. The section will conclude with a discussion on several studies whose findings reveal a need for more focused research on the differential impact of remedial education upon adult students.

The Impact on Retention/Persistence and Transfer

In an effort to overcome the methodological weaknesses of past research, Crisp and Delgado (2014) utilized recent national data on the 2003-2004 entering cohort and statistically controlled for both student- and institution-level influences. In so doing they attempted to decipher the causal impact of remedial education on persistence and transfer to a four-year institution among students who entered a community college seeking a four-year degree (Crisp & Delgado, 2014). Utilizing propensity score matching (PSM) to reduce selection bias, Crisp and Delgado (2014) bifurcated the student population in their national dataset into two groups: students who needed remediation and enrolled in remedial classes (developmental students) and students who needed remediation and did not enroll in remedial classes (non-developmental students). Outcomes analyses were then conducted for both groups utilizing hierarchical generalized linear modeling (Crisp & Delgado, 2014). PSM results confirmed that there is great variability between developmental and non-developmental students in terms of gender, race, first-generation status, high school GPA, and high school course-taking patterns (Crisp & Delgado, 2014). This finding, they concluded, confirms that "students who enroll in developmental courses are systematically different from community college students who do not remediate…" (p. 13). Therefore, researchers should, in the absence of randomized trials, attempt

to statistically control for differences between developmental and non-developmental students in studies which seek to understand the impact of remedial education (Crisp & Delgado, 2014).

With regards to the impact of remedial education on persistence, Crisp and Delgado (2014) found no significant relationship between remediation and same-institution persistence. This finding conflicts with prior research by Bettinger and Long (2009), who, using ordinary least squares and instrumental variables regression, found higher rates of retention among traditional-age students who took remedial courses across colleges in Ohio, compared to students with similar academic skill levels who did not take remedial courses. With regards to transfer, Crisp & Delgado (2014) found remediation to have a significantly negative impact on vertical transfer, especially for those students who enrolled in mathematics remediation. These findings conflicted with prior research done by Calcagno (2007), Calcagno and Long (2008) and Bettinger and Long (2005).

Crisp and Delgado (2014) conclude that "remediation may not be beneficial or necessary for promoting success for community college students" (p. 15). It should be noted, however, that their definition of success was relegated to persistence or transfer. While both are important components of student success, other researchers have defined success in terms of credit accumulation (Bettinger & Long, 2005b; Frye, 2014), performance in college-level courses (Bahr, 2010; Calcagno & Long, 2008), and degree completion (Bahr, 2008; Martorell & McFarlin, 2011; Frye, 2014). It should also be noted that the implications of Crisp and Delgado's (2014) findings are limited to a specific subset of remedial education students- specifically, students who are between 18-24 years of age who entered a community college with the expectation of transferring to a four-year institution.

The Impact on Credit Accumulation

Because credit accumulation is closely associated with progression and degree completion, and serves as a proxy for academic engagement, several researchers have studied remediation's impact upon the number of credit hours students attempt and complete. Using a longitudinal data set to track approximately thirteen thousand traditional-age students enrolled in Ohio's nineteen community colleges, Bettinger and Long (2005) found that students who took remedial math classes completed ten more credit hours over five years than students with similar attributes who did not take remedial math classes. English remediation, on the other hand, was found to have null effects on credit accumulation, as the study found no significant differences between students who took remedial English classes and those who did not (Bettinger & Long, 2005).

Findings by Martorell and McFarlin Jr. (2011), on the other hand, reveal remediation to have negative effects on credit accumulation in the first year of college attendance. Using a regression discontinuity approach which focused upon students just above and below the placement score, Martorell and McFarlin Jr. (2011) studied the effect of remediation on credit accumulation among approximately 100,000 students in community colleges throughout Texas. The researchers found remediation reduced credit accumulation by 2.4 credits in the first year of attendance (Martorell & McFarlin Jr., 2011).

A regression discontinuity design study by Calcagono and Long (2008) found that across 100,000 community college students in Florida, remedial math students earned between three and seven more credits than their academically-equivalent non-remedial peers. Remedial English students earned between one and three more credits than their academically-equivalent non-remedial peers (Calcagono & Long, 2008). The researchers, however, contend that while credit

accumulation is an important outcome, understanding whether or not those credits count towards a degree is more important. To that end, they found that when credits that were not applicable to a degree were excluded, the impact of remediation was null (Calcagno & Long, 2008).

While all three studies were conducted in rigorous fashion, they are limited in their ability to tell us about remediation's impact on credit accumulation for adult students (Bettinger & Long, 2005) and students far above and far below the placement cut score (Martorell & McFarlin Jr., 2011; Calcagono & Long, 2008). In a study with fewer limitations, Hodara and Jaggars (2014) attempted to understand the impact of remedial course sequence upon various student outcomes, regardless of age and regardless of how far above or below students were from the placement score. Using longitudinal data from the City University of New York System's six community colleges, Hodara and Jaggars (2014) studied the effects of shorter-length remedial sequences on overall credit accumulation. Using propensity score matching to control for potential selection bias, they found that students who took shorter-length remedial sequences in English completed two more college credits over three years than students with similar attributes who took longer English remedial sequences. No significant differences were found between students who took longer verses shorter math sequences (Hodara & Jaggars, 2014).

The Impact on Passing Gatekeeper Courses

To many researchers, the true test of remediation's effectiveness is whether or not students who are referred to remedial courses eventually pass the associated college-level course, oftentimes referred to as gatekeeper courses (Roska et al, 2009; Bailey et al, 2010; Bahr, 2010). Using a regression discontinuity design, Calcagno and Long (2008) found remediation to have no effect on the probability of successfully completing (defined as a grade of C or better) college-level math or college-level English courses among 100,000 community college students

in Florida. In a study of students across community colleges in California, Bahr (2010) found that the level of remedial math sequence (remedial depth) played a significant role in whether or not students remediated successfully (defined as earning a grade of D or better in the college-level class). Half of students entering at the highest level of the remedial math sequence remediated successfully, compared with 7% of those entering at the lowest level (Bahr, 2010). These findings are consistent with other studies which have shown remedial depth to have a significant effect on students' ability to remediate (Bailey et al., 2010; Jenkins, Jaggars, Roksa, Zeidenberg, & Cho, 2009; Hodara & Jaggars, 2014). In a follow up study in which successful remediation was defined as earning a grade of C or better, Bahr (2012) confirmed, through a series of logistic regression analyses, the findings from his 2010 study, including a confirmation of similar results in remedial English.

Bahr (2012) also discovered, when looking at remedial students' progression through the entire remedial sequence and into the gatekeeper course, that there was not a "large-scale 'exodus' from remedial math or remedial writing at any particular step of the sequence" and that "a majority of eligible students (albeit a declining majority) attempt the next step" (p. 676). In other words, remedial attrition did not seem to happen en masse at any particular juncture, but instead occurs gradually through each successive step in the process- a slow leak, as opposed to a ruptured pipe.

The Impact on Degree Completion

While some researchers have found remediation's effects to be limited to short term outcomes such as first to second year retention (Calcagno, 2007; Calcagno & Long; Crisp & Delgado, 2014), there have been several statewide studies on the impact of remediation on longer term outcomes, such as degree completion. Across all of these studies, the consensus seems

clear- remediation has null to negative effects on degree completion. Martorell and McFarlin Jr. (2011) found no evidence that remediation positively impacts degree completion within two-year institutions in Texas. This finding was consistent with a similar study conducted by Calcagno and Long (2008), which found math remediation to have null effects and English remediation to have negative effects on certification and degree completion among community college students in Florida. Likewise, Bettinger and Long (2005), in a study of traditional-age students across Ohio's community colleges, discovered math and English remediation to have null effects on degree completion.

A recent study by Bahr (2013) offers a closer look into remediation's impact upon degree completion by asking a heretofore unasked question within the remedial education literature. Previous studies (Bahr, 2010, 2012a) revealed that many students who drop out of the remedial math sequence (i.e., students who fail to remediate) remain enrolled in the community college, but often fail to earn a credential. Bahr (2013) wondered why such students do not pursue alternative credentials, such as career and technical certificates, which often do not require completion of college-level math. Based on previous research by himself and others, he hypothesized that these students do not adjust their academic paths due to difficulty navigating to the alternative path, and that declining participation and academic performance eventually lead them to dropping out as opposed to credential completion (Bahr, 2013).

To test his hypotheses, Bahr (2013) analyzed the course-taking patterns, average course credit load, and average rate of course success, both before and after exiting the remedial math sequence, of 79,545 students within the fall 2002 first-time cohort across California's 112 community colleges (Bahr, 2013). He also utilized data from the National Educational Longitudinal Study (NELS) to estimate, on a national scale, how frequently students remain

enrolled in community colleges after unsuccessful remediation (Bahr, 2013). Two statistical

techniques were used, multilevel logistic regression and simple ordinary least squares linear

regression (Bahr, 2013).

With regards to the prevalence of students remaining enrolled in the community college

after failing to remediate, Bahr (2013) found that a majority of students in California (68%) and

a majority nationally (60%) did so. Furthermore, he found that, on average, students in California

stayed enrolled in the community college 2.0-3.8 additional semesters following exit from the

remedial math sequence (Bahr, 2013). More troubling however is the fact that 84% of these

students ultimately left postsecondary education without a credential (Bahr, 2013). These

findings confirmed results of previous studies (Bahr, 2010, 2012a).

With regards to why this phenomenon occurs, Bahr (2013) confirmed his three

hypotheses. He found that although vocational course taking increased following exit from the

remedial math sequence, there is not a "wholesale shift toward vocational coursework…that

would be necessary for most students to complete a certificate in their limited remaining time in

the community college" (Bahr, 2013, p. 196). In addition, he found course credit load and course

success declinations following exit from the remedial sequence (Bahr, 2013). Average course

success decreases were especially pronounced for students who began remediation within the

lowest levels of the remedial sequence (Bahr, 2013).

Bahr's (2013) findings have implications for research. He asserts that prior studies on the

outcomes of remedial education have centered upon understanding its impact on the likelihood

of completing the associated college-level course, associate-degree completion, or transfer (Bahr,

2013). While it is important to understand how effective remedial education is with respect to all

three of these outcomes, we "can be certain there always will be a fraction of students who exit

the remedial math sequence without achieving college-level math competency" (Bahr, 2013, p. 195). Thus, there is a need for research that can inform policy makers and practitioners on effective practices for ensuring that all students, regardless of their ability to remediate, leave college with some type of viable credential. To that end, Bahr (2013) advocates for the career and technical certificate, a credential that oftentimes does not require college-level math or English and can be completed within a relatively short amount of time. Bahr's (2013) study also makes a compelling argument for research on approaches to encourage non-remediated students to remain engaged in college. The overall observed "gradual 'slippage' from college" (operationalized as lower course credit loads and decreased course success in the aftermath of exiting remediation) may be just as much to blame for students' departure without a credential as their inability to navigate into a certificate program (Bahr, 2013, p. 196).

Remediation's Impact on Adult Students

Despite the abundance of literature examining the impact of remedial education, very few studies delve into the impact of remedial education on adult students specifically. This is despite the fact that several researchers have found adult students to be more likely to have remedial needs than their traditional-age counterparts (Calcagno et al, 2007; Crisp & Nora, 2010; Crisp & Delgado, 2014). The same kind of rigorous research described above is therefore needed to understand any differential impact of remediation upon this group. A review of the literature found only one study (Calcagno et al., 2006) which framed its research questions around the theory of differential impact of various enrollment pathways (such as remediation) on older verses younger students in the community college setting. Utilizing a discrete-time-hazard model, the researchers found that although remediation decreases the odds of graduation for all students, older students' odds are less negatively impacted than are the odds of younger students.

The researchers also found that older students were more likely to need remediation as a short-term refresher as opposed to a semester-length, traditional format course, especially in developmental math (Calcagno et al, 2006).

Other studies have included unexpected findings on remedial education outcomes for adult students, despite it not being the main focus of the study. In a qualitative study of the experiences of remedial education students in community colleges, Johnson (2012) was surprised to learn of tensions between younger and older students enrolled in the same remedial course, stating, "I did not anticipate the strong emotions that arose in relation to older and younger students" (p. 98). She reports, "Younger and older students spoke from opposite perspectives about the age divide and how it affected the learning environment" (Johnson, 2012, p. 97). She goes on to say, "There was mutual dissatisfaction between younger and older students and a mutual feeling that the other slowed down the class and/or disrupted learning" (Johnson, 2012, p. 97). In response, she advocates for more "age-specific supports" (p. 166). Bailey et al. (2010) found that older students were less likely than their traditional-age counterparts to complete remedial coursework. Calcagno et al (2007) discovered that older students were overrepresented in remedial mathematics courses. In a study of persistence patterns among remedial math students in Kentucky's Community College System, Davidson and Petrosko (2015) found age to be a significant predictor of semester-to-semester persistence (with persistence being defined as enrollment in the subsequent term, transfer, or being awarded a diploma, certificate, or degree), with younger students being much more likely to persist than adult students.

Bean and Metzner's Nontraditional Student Attrition Model

As stated previously, this study conceptualized remediation as an attrition process, and was framed by Bean and Metzner's (1985) Nontraditional Undergraduate Student Attrition

Model. The model, depicted in Figure 1, portrays a drop-out decision tree which is influenced, in a number of ways by various constructs and outcomes. The four constructs, background variables (age, hours enrolled, educational goals, high school performance, ethnicity, and gender), academic variables (study hours, study skills, academic advising, absenteeism, major/job certainty, course availability), environmental variables (finances, hours of employment, family responsibilities, opportunity to transfer), and social integration variables (memberships, faculty contact, school friends) have varying levels of direct and indirect impacts upon the nontraditional students' academic and psychological outcomes and intent to leave, culminating in a decision to either stay enrolled or drop out.

Figure 1. Bean and Metzner's Attrition Model, 1985
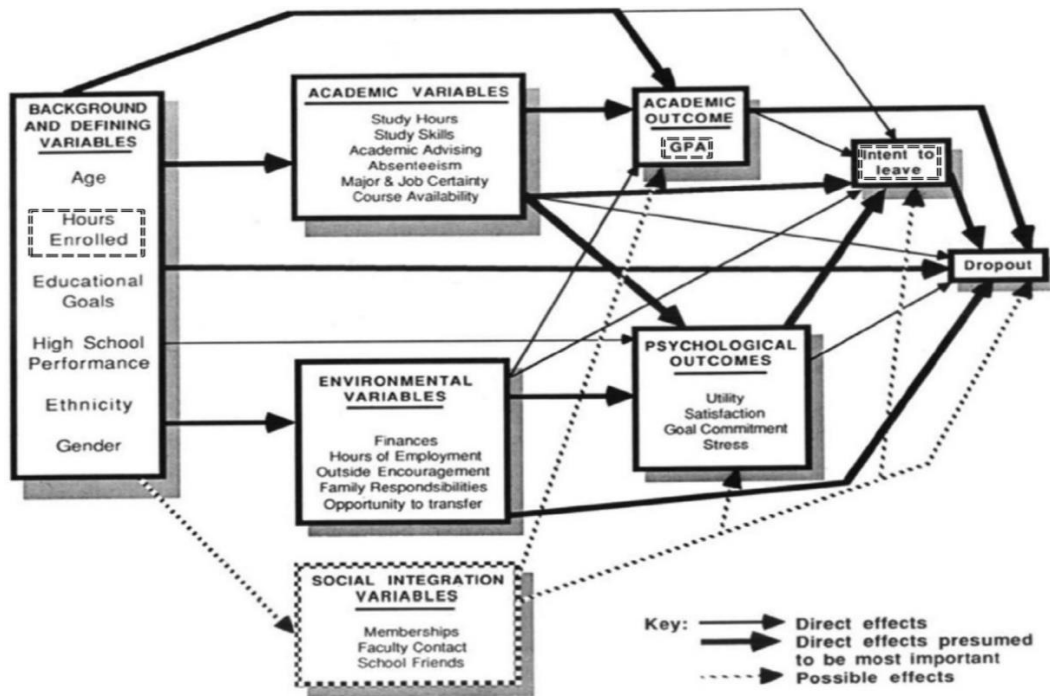
Development of Bean and Metzner's Model

The impetus for the development of Bean and Metzner's (1985) Model was an analysis of the student attrition models of Spady (1970), Tinto (1975), and Pascarella (1980), all of which identified social integration into the college (participation in college-sponsored extracurricular

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activities, interactions with faculty outside of class, and friendships with other college students)

as a major explanatory variable in whether or not a student decides to remain enrolled in college.

Bean and Metzner (1985) hypothesized that socialization is not as significant of a factor for

nontraditional students. They defined nontraditional students as students who have one of the

following characteristics: 24 years of age or older, do not live on campus (i.e., commuter), or

attend college part-time. Adult students (those 24 years of age or older), they surmised, have

already "developed self-control and values typically identified with maturity" and are therefore

"less susceptible to socialization than their nontraditional counterparts" (p. 488). In addition,

they contended that commuter and part-time students spend less time on campus by virtue of

their commuter and part-time status and therefore have less opportunity to engage in college-

sponsored extracurricular activities, or interact with faculty and their collegiate peers. They

therefore concluded that an attrition model for nontraditional students, which puts less emphasis

upon the role of socialization, was warranted. Several studies at community colleges and other

predominantly commuter institutions have since validated Bean & Metzner's (1985) assertion

that for nontraditional students, academic integration is a much stronger predictor of retention

than is social integration (Borglum & Kubala, 2000; Nora, 1987; Townsend & Wilson, 2008-

2009; Pascarella & Chapman, 1983a, 1983b).

In developing their Model, Bean and Metzner (1985) consulted a vast literature base

consisting of sixty-nine empirical and descriptive studies of traditional and nontraditional

students, and attrition. The studies took place at various types of institutions throughout the

United States. In so doing they concluded that nontraditional students' decision to stay enrolled

in college is based primarily on: cumulative collegiate GPA, environmental variables, intent to

leave (i.e., the student's long-term goals with regards to enrollment at a specific institution), and

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background and defining variables. In sum, the Model surmises that students with poor cumulative collegiate GPAs will drop out at a higher rate than students with better GPAs, and that collegiate GPA is highly dependent upon high school GPA. In addition, intent to leave is expected to be heavily influenced by psychological outcomes and academic variables. Background and defining variables, especially high school performance and educational goals, are theorized to have a significant effect on attrition, but these effects may be mediated by academic and environmental variables. Lastly, environmental variables are expected to have a significant effect upon attrition, and are theorized to be heavily influenced by several background and defining variables (age, ethnicity, and gender). While social integration variables are included, they are believed to have minimal impact upon nontraditional student attrition.

Because Bean and Metzner's (1985) Model is a synthesis of prior research that spanned student populations and institutional type, it is an extremely flexible model. This makes it preferable to other nontraditional student attrition models, such as Stahl and Pavel's (1992) Community College Retention Model, because it can be used to replicate and expand studies on nontraditional student attrition, regardless of institutional setting. The research used in the development of Bean and Metzner's (1985) Model included studies of nontraditional students in two-year commuter colleges, commuter-oriented four-year institutions, and residence-oriented four-year colleges. The application of the Model to community colleges in Louisiana is therefore justifiable. It is preferable to other attrition models as future studies on the topic may be expanded beyond the community college setting.

The Model also allows for the study of particular subgroups of nontraditional students. In fact, the authors advocate for such analyses, stating that while the "process of attrition is expected to be similar for nontraditional students regardless of their institutional setting or

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student subgroup affiliation" the most important variables will likely differ based upon subgroup (Bean & Metzner, 1985, p. 530). They argued for separate analyses of subgroups because they felt it would reduce "potentially confounding heterogeneity in research samples containing nontraditional students" (p. 528). As stated above, all students in this study were nontraditional (commuter) students. The study created a subgroup by identifying those who were referred to remedial education. That subgroup was then further delineated by splitting the subgroup into two additional subgroups (adult and traditional-age). Separate analyses, as advocated by Bean and Metzner (1985), were conducted for each subgroup of nontraditional student.

Bean and Metzner (1985) developed their model with the intent of guiding future research on nontraditional student attrition, asserting that the Model could "…provide a framework for understanding past studies and should serve as a guide for conducting future ones" (p. 530). The Model has been utilized in contemporary dissertations and peer-reviewed research, both qualitative and quantitative, to study attrition among nontraditional students in general (DeRemer, 2002; Maroney, 2010) among remedial education students specifically (Cunningham, 2010; Frye, 2014), and to compare the persistence patterns of traditional-age and adult students (Sorey & Duggan, 2008). Each of these studies utilized specific aspects of Bean and Metzner's (1985) Model as trying to incorporate all constructs of the Model (Bean and Metzner, 1985) into a single study would likely be unwieldy.

Using Bean and Metzner's (1985) Model (in addition to other student attrition models) as a conceptual framework, DeRemer conducted a series of focus groups with nine adult students enrolled at various campuses in Texas. He concluded that interactions with institutional staff, personal finances, and unexpected crises play a major role in adult student attrition (DeRemer, 2002). DeRemer's (2002) findings thus support Bean and Metzner's (1985) theory that

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environmental variables (such as personal finances and family crises) and psychological outcomes (in this case satisfaction with institutional staff members) have an impact on nontraditional student attrition.

Maroney (2010) focused exclusively upon the role that the psychological outcomes (specifically stress) of Bean and Metzner's (1985) Model play in attrition. She studied the effect of stressors and coping mechanisms on attrition among adult students enrolled in a single institution in Pennsylvania (Maroney, 2010). Using survey research design and logistic regression analyses, she found work stress combined with passive coping mechanisms to be correlated with a higher probability of attrition (Maroney, 2010). Specifically, Maroney (2010) found that for each unit increase in work stress, chances of persistence decreased by 36% (Exp$B=$ .64, p $<$.05) and that for each unit increase in passive coping mechanisms, chances of persistence decreased by 75% (Exp$B=$ .25, p$<$.05).

Cunningham (2002), using Bean and Metzner's (1985) model as a broader framework and elements of Stahl and Pavel's (1992) Community College Retention Model as an operational framework, developed a survey to assess the effects of academic and environmental variables on remedial and non-remedial education students' intent to persist at a single community college in Georgia. The survey yielded 506 responses from three groups of students- students enrolled in remedial education (remedial students), students who completed remediation and were enrolled in college-level courses (remediated students), and students who were never referred to remediation (non-remedial students). With regards to academic variables, using correlation analysis, Cunningham (2002) found moderate correlations between class attendance and intent to persist among remedial students (r= .300, p < .01), remediated students (r= .362. p < .01), and non-remedial students (r= .254, p < .01). With regards to environmental variables, Cunningham

(2002) found weak to moderate correlations between: hours of employment and intent to persist among remedial students (r= .200, p < .01); outside encouragement and intent to persist among remediated students (r= .313, p < .05) and non-remedial students (r= .366, p < .05); finances and intent to persist among remedial students (r= .237, p < .01) and remediated students (r= .283, p < .01); and opportunity to transfer and intent to persist among remediated students (r= .338, p < .05).

Guided by a synthesis of Bean and Metzner's (1985) Model and Tinto's (1993) Theory of College Departure, Frye (2014) conducted a study of remedial math completers who completed and did not complete college-level math in community colleges in North Carolina. Using propensity score matching, Frye (2014) statistically mimicked an experimental design in an effort to understand the impact of remedial math education and subsequent college-level math completion on college credit accumulation, completion, and transfer. Results indicated that students who successfully completed remedial math and the associated college-level course (i.e., students who were presumed to be remediated) completed, on average, 25 more college credits, earned significantly more associate degrees, and were more likely to transfer than their non-remediated counterparts.

Bean and Metzner's (1985) Model also influenced Sorey& Duggan's (2008) study of differential predictors of persistence between two randomly selected samples of adult and traditional-age students in a multi-campus community college in Virginia. Combining demographic, outcome, and survey data, the researchers used two-way contingency table analysis and discriminate analysis to determine differential predictors of persistence between the two groups. Their findings contradicted Bean & Metzner's (1985) assertion that social integration has less influence on adult student persistence than academic integration and that the

converse is true of traditional-age students. Their findings revealed just the opposite. Social integration had a large influence (.821) on the persistence of adult students and minimal influence (.050) on traditional-age students within the discriminate function analyses. In addition, academic integration had a significant influence (.446) on the persistence of traditional-age students and was found to be the "least significant of all predictors included in the discriminate analysis for adult students" (Sorey & Duggan, 2008, p. 92). The authors also found the discriminate analysis for adult students to be much more complex than for traditional-age students, meaning that a greater number of variables seem to influence adult student persistence. It should be noted however that the response rate to the study's survey was low and the authors contend that "the reliability of the present study is questionable" (Sorey & Duggan, 2008, p. 93).

Exploring Factors that Affect Attrition within the Remedial Process

Conceptualizing remediation as a process and understanding that failure to complete remediation and the associated college-level course prohibits students from progressing in their curriculum (as most degree programs require passage of a basic college-level mathematics and English course); several researchers have focused upon the remedial process itself. In so doing, they have sought to examine where within the process students are lost and how that loss can be statistically predicted (Bahr, 2010; Bailey et al., 2009; Bahr, 2012; Frye, 2014). These studies have found that certain demographics (especially race, age and gender), financial need, as well as the degree of remediation the student needs, play a significant role in whether or not a student will progress successfully through the remedial process.

Utilizing logistic regression and defining successful remediation as passage of a college-level course with a grade of C or better, Bahr (2010) found "large and statistically significant racial differences in the likelihood of remediating successfully" across community colleges in

California (p. 220). Specifically, he found Blacks and Hispanics face "significant disadvantages in the likelihood of successful remediation" (p. 227). He points out however that race itself is not a determining factor, but instead a proxy for other attributes that affect remedial attrition, most notably math skill level at college entry (i.e., the level of deficiency a student has upon entering college). To this end, Bahr (2010) found math skill level to be highly correlated with successful remediation, with those with the greatest deficiency having lower odds of successful remediation. He points out that Blacks and Hispanics begin college, on average, with greater math deficiencies (Bahr, 2010).

Utilizing nationwide data and multivariate analysis, Bailey et al (2009) found that students referred to remedial education are more likely to not enroll in remedial coursework than they are to enroll in the coursework and subsequently fail or withdraw. In other words, remedial attrition is due in large part to students not starting the process in the first place. In addition, the researchers studied the likelihood of completing remedial coursework across students who were referred to various levels (depths) of remediation. They found, holding remedial depth constant, that: female students had significantly higher odds of progressing successfully through remedial coursework than their male counterparts; older students had lower odds of completing remedial coursework than younger students, especially within reading remediation sequences; Black students had lower odds of completing than White students; full-time students had greater odds of completing remedial coursework than part time students; and students majoring in vocational areas had lower odds of completing than students majoring in liberal arts (Bailey et al, 2009). The researchers concluded, "Men, Black students, older students, and those attending part time or studying in a vocational area had lower odds of progressing through their developmental sequences" (Bailey et al, 2009, p. 22).

Bahr (2012), utilizing a series of logistic regression models and student-level data from across the California community college system, studied the course-taking patterns and outcomes of remedial math and writing students who entered remedial course sequences at varying levels. He bifurcated the study population into low-skill (those who entered the remedial sequence at the lower levels) and high-skill (those who entered the remedial sequence at higher levels). When comparing low-skill and high-skill students, Bahr (2012) found an increased likelihood among low-skill students to delay the first attempt at remediation (p. 683). In turn, he found "students who delayed their first remedial course were less likely to pass this course, less likely to attempt the second step of the remedial sequence, and more likely to delay this second step if they attempted it," and so on (p. 686). In addition, although more pronounced among low-skill students, Bahr (2012) found what he called "escalating nonspecific attrition" with each successive step within the remedial process among both groups (p. 684). In other words, holding all other variables equal, as remedial students moved through the process (whether they were low-skill or high-skill) an increasing number of them failed to attempt the next step, whether that next step was enrollment in the successive remedial course in the sequence or enrollment in the associated college-level course. Even among students who were passing the courses, there was an escalation in attrition at each juncture (Bahr, 2012). In this vein, low-skill students were at a decided disadvantage as they had more steps and junctures to navigate on their road to the college-level course than did their higher-skill counterparts. Bahr (2012) also found evidence of what he termed "course-specific attrition," suggesting that certain courses within a sequence account for a significant portion of attrition (p. 684). Within the remedial math sequence, Bahr (2012) found evidence that beginning algebra accounted for a significant portion of attrition due

to non-passing grades. He found no particular courses in the writing sequence, however, that accounted for a significant portion of course-specific attrition.

In a study of community college students across North Carolina who took a remedial math course, Frye (2014) found gender, race, Pell recipient status, and first term grade point average to result in a robust overall model for predicting whether or not a student would complete the college-level math course with a grade of C or better (-2 Log Likelihood= 2282.99, chi-squared= 110.26, $p < .001$, Nagelkerke R Squared= .075). Specifically, she found that: female students were 37% more likely to pass college-level math; Black students were 40% less likely to pass college-level math; Pell recipients were 27% less likely to pass college-level math; and students with higher first term grade point averages were 24% more likely to pass college-level math (Frye, 2014).

Synthesis

The above literature review includes many strands of literature that, in the aggregate, formed a conceptual framework (depicted in Figure 2) in which this study was developed and implemented. The framework consists of two contextual layers- the peripheral context and the central context. The peripheral context includes elements that the researcher was aware of throughout the study and revisited to evaluate findings and to derive potential policy implications, but that were not directly driving any particular methodological decisions. The peripheral context, although still bounded within the framework, is depicted in the outer realm, to denote its presence in the background of the study. The central context includes elements that were germane to the study itself and served as a guide in methodological decision-making. The central context is represented in a 3-D form to denote its prominence over the peripheral context

and in a cone-shaped form to convey that the literature base contained within it narrowed the study towards the theoretical framework.

Figure 2. Conceptual Framework

Peripheral Context:

Historical perspectives on remediation
Contemporary issues surrounding remediation
Community colleges' role, scope, mission and student body
The differential needs of adult students
Louisiana's remedial education policy framework

The Central Context:

Prior research on the impact of
remedial education on various
postsecondary outcomes

Remediation as a process

Factors affecting remedial attrition

Bean &Metzner's (1985)
Nontraditional Undergraduate
Student Attrition Model

CHAPTER 3: METHODS

This study conceptualized the remedial math process as an attrition process in which students either progress onto the next stage, or they do not. Also understanding that age is a research-worthy variable (Adelman, 2005; Choy, 2002a) that has been heretofore understudied within the remedial education literature, this study had particular emphasis upon the effect age has on the remedial math process. Many researchers have derived student attrition models by calculating (regressing) the likelihood of attrition based upon student background factors such as age, race, gender, and other pre-college variables such high school GPA (Choy, 2002b; Pascarella &Terenzini, 2005; Bailey et al, 2009), often referred to as an input-output model (Bahr, 2013). Bean and Metzner's (1985) Model also includes pre-college factors but posits that other factors such as college GPA and environmental variables such as finances, may also affect attrition post-college entry. To better understand the influence age has upon various remedial math outcomes, the points at which students fail to progress within the remedial math process, and to statistically model the pre- and post-college entry predictors of that attrition, this study utilized multiple logistic regressions to answer the following research questions:

(1) What are the most significant pre- and post-college entry predictors of remedial math education outcomes (enrollment in a remedial math course following referral, completion of the remedial math sequence, enrollment in a college-level math course, and completion, with a grade of C or better, of a college-level math course)?

(2) Is age a significant predictor of various remedial math education outcomes (enrollment in a remedial math course following referral, completion of the remedial math sequence, enrollment in a college-level math course, and completion, with a grade of C or better, of a college-level math course)?

Data used in this study was longitudinal, student-level data from ten public community colleges in Louisiana, all members of the Louisiana Community and Technical Colleges System (LCTCS). While the LCTCS consists of thirteen institutions, three of those institutions are, or were during the academic years included in this study, technical colleges. Students at the three technical colleges were excluded from the study because of the specialized curricula at those institutions, which focuses more upon short-term workforce training. Three of the ten community colleges in the study are considered urban institutions, with the remainder being rural. The study population consisted of all first-time, associate degree-seeking students who were referred to remedial math courses (based upon their ACT or COMPASS exam scores) during the fall 2013 and fall 2014 semesters. All ten of the community colleges utilize the Louisiana Board of Regents' statewide placement policy and cut scores (Louisiana Board of Regents, 2016) for the referral of students to remedial education courses.

This study utilized as its theoretical framework Bean and Metzner's (1985) Nontraditional Undergraduate Student Attrition Model. The use of theory in quantitative research is a deductive process. The researcher "…advances a theory, collects data to test it, and reflects on its confirmation or disconfirmation by the results" (Creswell, 2014, p. 59). In this sense, the theory, borne from the literature base on a particular subject, serves as a "framework for the entire study" (Creswell, 2014, p. 59). The theory provides a rationale for the selection of variables and for the conceptualization of the relationships between those variables. In this vein, Bean and Metzner's (1985) Model was utilized to guide the methodological approaches (data collection and data analysis) of this study. Although the study utilized quantitative methods, the Model could be utilized to guide either qualitative or quantitative research (Bean & Metzner, 1985). This chapter will discuss the study population, independent and dependent variables, data

set construction, data cleaning and transformation, the testing of the assumptions of logistic regression, and research design.

Study Population

According to the Louisiana Board of Regents' Academic Affairs Policy 2.18 (Louisiana Board of Regents, 2016), students must have ≥19 on the math sub-section of the ACT or ≥40 on the Algebra COMPASS exam to be placed into college-level mathematics (i.e., avoid math remediation). The study population consisted of all first-time, associate degree-seeking college students who were referred to math remedial education courses (based upon their inability to attain the Board of Regents' placement cut scores on the ACT or COMPASS exam) during the fall 2013 and fall 2014 semesters (N= 11,203). These two cohorts of students (fall 2013 starters and fall 2014 starters) were tracked over two academic years, or five semesters (the fall 2013 cohort was tracked through spring 2015 and the fall 2014 cohort was tracked through spring 2016) across all ten colleges within the study.

The decision to study only first-time students was based upon the assumption that students with prior postsecondary experience may enter the remedial process with different expectations or beliefs (based upon their prior experience) than students with no prior experience, and that those expectations or beliefs may influence their behaviors. The use of first-time cohorts is a common practice within the remedial education research literature for this reason (Bahr, 2010; Bahr, 2012; Bahr, 2013; Bettinger & Long, 2009; Crisp & Delgado, 2014). For the purposes of this study, *first-time college student* denotes those students who: enrolled in for-credit coursework for the first time in fall 2013 or fall 2014, did not transfer in any postsecondary course credit or hold a postsecondary degree at time of entry, or were not concurrently enrolled in high school.

The decision to exclude non-degree-seeking students from the study (i.e., focus only upon degree-seeking students) was a methodological decision made for the purposes of ensuring that the study population was as homogenous as possible with regards to intent. Including non-degree-seeking students who enrolled solely for the purpose of taking a few courses for job enhancement, for example, would not be a fair comparison to students who matriculate with the intention of completing a degree. Furthermore, any practical or policy implications derived from this study's findings would likely be geared towards the improvement of remedial education for the purposes of getting students through the remedial process in order for them to complete a credential.

Variable Selection

With regards to specific variable selection, the study was guided by Bean and Metzner's (1985) Model, but deviated in several significant ways, which will be discussed below. Bean and Metzner's (1985) Model is comprehensive and therefore includes a large number of variables. Tinto (1982) posited that there is often a tradeoff between maximizing a model's predictive power (through the inclusion of a large number of variables) and the loss of "clarity in explanation" (p. 688). Inclusion of every variable in Bean and Metzner's (1985) Model within the study would have been statistically unwieldy. Therefore, careful selection of variables, with a preference for clarity in explanation over maximization of the model's predictive power, was the objective.

Independent Variables

Bean and Metzner's (1985) Model hypothesizes that nontraditional student attrition is influenced primarily by cumulative collegiate GPA, environmental variables, intent to leave, and background and defining variables. Bean and Metzner (1985) assert that concentration on single

parts of the Model, as opposed to the entire model, is acceptable (1985). Thus, this study focused only upon the effects of background and defining variables, cumulative collegiate GPA, and environmental variables, three of the four constructs believed to most heavily influence nontraditional student attrition (Bean & Metzner, 1985). Students' intent to leave was not included in this study as the researcher did not have access to data on students' personal intentions.

Academic variables and psychological outcomes, two constructs that are considered mediating variables within Bean and Metzner's (1985) Model were not included in this study. Academic variables, which are theorized within Bean and Metzner's (1985) Model to have mediating effects upon cumulative collegiate GPA and intent to leave, were not included within this study as the researcher did not have access to individual students' study habits, study skills, extent/quality of academic advising, class attendance records, or perceptions on major/job certainty or course availability. Psychological outcomes, theorized by Bean and Metzner (1985) to affect attrition through intent to leave were not included within this study either as the researcher did not have access to individual students' perceptions on the utility of their education, satisfaction with the college, goal commitment, or stress.

Background and defining variables. Bean and Metzner's (1985) Model includes the following background and defining variables: age, hours enrolled in college (full-time or part-time status during the first semester of enrollment), educational goals (degree or non-degree-seeking status), high school performance, ethnicity, and gender. For each student in the study, the following background and defining variables were collected: age (upon entry to the college), full or part-time status during the first semester of enrollment, cumulative high school GPA,

ethnicity/race, and gender. Each student within the study was an associate degree-seeking student, so no variation in educational goals existed within the study population.

Bean and Metzner (1985) encourage researchers to add to and mold the Model by cautioning against "relying exclusively on the model developed" to study the attrition of any subgroup (p. 529). Thus, an additional background and defining variable not included in Bean and Metzner's (1985) Model was included in this study as an independent variable because it was hypothesized to be relevant based upon the existing literature on remedial education (Calcagno & Long, 2008; Bahr, 2008). This variable was the extent of remedial need, operationalized as the numeric distance from the cut score used to place the student in remedial education (Calcagno & Long, 2008; Bahr, 2008). This additional variable was added to the background and defining variables within the study's theoretical framework as it is a characteristic that the student began the remedial process with, pre-entry to the college.

Environmental variables. Bean and Metzner's (1985) Model includes the following environmental variables: finances, hours of employment, outside encouragement, family responsibilities, and opportunity to transfer. The researcher did not have access to individual students' hours of employment, outside encouragement, family responsibilities, and opportunity to transfer. Thus, this study included only one environmental variable - total dollar amount of unmet financial need. This was derived by subtracting the student's total cost of attendance (tuition, fees, books, supplies, room and board, transportation, and personal expenses) minus the total dollar amount disbursed to the student (including any grants, scholarships, loans, or Work-Study aid). This calculation is stored within the BANNER data base for each student within the study population who completed a Free Application for Federal Student Aid (FAFSA) for the 2014 or 2015 aid year. This particular environmental variable was chosen because it will provide

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insight into the upfront, out-of-pocket cost of attendance borne by the student, which may affect the students' ability to remain enrolled in college and to progress through the remedial process(The Education Advisory Board, 2015; Terriquez et al, 2013; Hossler et al, 2008). Having to bear a large financial burden could affect the number of hours a student must work or the number of credit hours the student can take.

Cumulative collegiate GPA. Bean and Metzner (1985) hypothesize that, students with poor academic performance (low collegiate GPA) are more likely to drop out than are students with higher GPAs. For this reason, it is included in their Model (Bean & Metzner, 1985) and was included in this study. The cumulative collegiate GPA (from all for-credit coursework taken by the student over the course of the two academic years following initial fall enrollment) was collected for each student in the study population.

Dependent Variables

With regards to dependent (outcome) variables, Bean and Metzner's (1985) Model includes one operational definition of attrition: failure to maintain enrollment in college from one semester to the next. They acknowledge the limitations this poses and state that researchers need to "choose an operational definition of attrition that is appropriate for the research problem being investigated" (Bean & Metzner, 1985, p. 489). This study had four operational definitions of attrition that are appropriate to studying attrition within the longitudinal process of remedial math education, including: failure to enroll in any remedial math course (Grubb & Cox, 2005); failure to complete the remedial math sequence (Bahr 2010b, Bailey et al, 2010); failure to enroll in a college-level math course (Roska et al, 2009); failure (defined as any grade other than A, B, C or Pass) of the college-level math course (Calcagno & Long, 2008, Bahr 2010b).

It should be noted that the colleges within the study have varying levels of math remediation, resulting in a sequence of remedial math courses, ranging from two to three courses. Students are referred to a level of math remediation based upon the extent of their remedial need (as determined by the numeric distance of their ACT/COMPASS score from the placement cut score of 19/40). For purposes of this study, a student was considered to have completed the remedial math sequence if they successfully completed (defined as receiving a Pass or a grade of C or better) the highest remedial math course at that particular institution. In addition, students can, and often do, take courses more than once. Many colleges within this study employ what is referred to as *repeat and delete* policies, in which the grades students earn on their second attempt in a class replace the grades they earned during their first attempt. This study used only the latest grades, which in some cases may reflect a student's second, or possibly third or fourth, attempt. In addition, students often withdraw (grade of W) from a course, or receive an incomplete grade (grade of I) which they may subsequently fail to resolve. Consistent with other research on remedial education outcomes (Bahr, 2013), both W and I grades were treated as a failure to remediate for purposes of this study.

Data Set Construction

The researcher, by virtue of her employment with the LCTCS, had access to all of the data utilized within this study. The researcher obtained written consent from the LCTCS to utilize these data for the purposes of this study (APPENDIX B). All of the student-level data utilized was housed within an Ellucian BANNER database, a proprietary student information system. The researcher, with the assistance of LCTCS Information Technology (IT) staff, extracted the data from the BANNER system through a series of database queries written using

SQL. The researcher then constructed an external data set within IBM's Statistical Package for the Social Sciences (SPSS), version 24. All analysis was conducted within SPSS.

The researcher first identified the initial study population: all first-time, associate degree-seeking students who were referred to remedial math during the fall 2013 and fall 2014 semester across the ten colleges included in the study. To do so, the researcher extracted from the BANNER data base all students with an admission code of "1" that were enrolled in an associate degree program for both the fall 2013 and fall 2014 semesters. Admission code "1" denotes that the student has no prior college enrollment, as verified through the National Student Clearinghouse. This resulted in a population of 25,209 first-time, degree-seeking students. The researcher then appended each student's highest ACT or COMPASS test score. The highest score was collected because students often take the ACT and/or the COMPASS multiple times, and for purposes of placement, institutions use the highest test score. In addition, all records with a missing test score (n= 9,011) were removed from the data set, resulting in a population of 15,198. It is not uncommon for students to enroll in a college and never turn in an ACT score or take the COMPASS exam. Neither is mandatory for admission and failure to have a placement test score on file becomes an issue only if the student attempts to enroll in a college-level math or English course. Last, the researcher removed all records that met the minimum cut score for placement into college-level math. This resulted in a final analytic population of 11,203.

Once the initial study population was identified, the researcher appended the date of birth, ethnicity/race, and gender, all of which were entered by the student on their application to the college. The researcher then added cumulative high school GPA (which is obtained from the Louisiana Department of Education through the Statewide Student Transcript System and stored within BANNER) and cumulative college GPA (the cumulative GPA for all for-credit

coursework the student earned during the two years included in the study). Then, the researcher appended the total number of credit hours the student was enrolled in during the first semester of college. Lastly, the researcher appended the unmet financial need calculation, which is stored within BANNER for each student that completes a FAFSA.

Once all independent variables were collected, several were transformed. Date of birth was transformed into age by subtracting the date of birth from August 1, 2013 (for those students who entered college in the fall 2013 semester) and from August 1, 2014 (for those students who entered college in the fall 2014 semester). Then, a new variable (extent of remedial math need) was created. To ascertain the extent of each student's remedial need, COMPASS scores were converted to ACT scores, utilizing the ACT/COMPASS concordance table published by ACT, (ACT, 2016) and were subtracted from the cut score of 19. Finally, students who were enrolled for $\geq$ 12 credit hours were coded as "1" for full-time. Those that were enrolled for $<$ 12 credit hours were coded as "0" for part-time.

The researcher then collected each of the four outcome variables. Within BANNER, all remedial courses are identified with a remedial "flag." To determine whether or not a student enrolled in any remedial math course during the two academic years following their college entry, an SQL program was written to search each student's academic record for any course with a remedial flag that also contained the word MATH in the course prefix. The SQL program returned a "1" for those who were found to have attempted (not necessarily completed) a remedial math course, and a "0" for those who did not. The researcher then determined, by reviewing college catalogs, the highest remedial math course at each of the ten colleges. An SQL program was written to search each student's academic record in BANNER for a grade in those courses. If the student earned a grade, the program returned the grade. If the student did not earn

a grade, the program returned a blank on that student's record. To determine whether or not a student attempted any college-level math course, an SQL program was written to search each student's academic record for any course without a remedial flag that also contained the word MATH in the course prefix. The SQL program returned a "1" for those who were found to have attempted (not necessarily completed) a college-level math course, and a "0" for those who did not. Last, an SQL program was written to search each student's academic record in BANNER for a grade in any college-level math course. If the student earned a grade, the program returned the grade. If the student did not earn a grade, the program returned a blank on that student's record.

Once all outcome variables were collected, several were transformed. If students earned a C or better or a P (for pass) in the highest remedial math course, they were coded as a "1" for completing the remedial math sequence. If they did not, they were coded as a "0." If students earned a C or better or a P (for pass) in a college-level math course, they were coded as a "1" for completing a college-level math course. If they did not, they were coded as a "0."

Data Cleaning and Transformation

Following data set construction, the researcher employed pre-screening techniques to detect and address missing data (Osborne, 2013). Output from the *SPSS: Multiple Imputation-Analyze Patterns* function revealed two variables (high school GPA and unmet financial need) had missing values, resulting 4,182 cases having incomplete data. Overall, 4,736 cells (3%) were blank, with 2,049 (18.3%) missing high school GPA and 2,686 (24.0%) missing unmet financial need. According to Osborne (2015), once missing data are detected, it is important to "come to a conclusion about the *mechanism of missingness*- in other words, the hypothesized reason for why the data are missing" (p. 363). Because all colleges within the study are open-

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admission, many of the college admission offices do not record high school GPA on all incoming

student records as it is not a determining factor in admission. While the offices do attempt to

collect this information, some data goes uncollected, and it is plausible that it is not collected in

random fashion. With respect to the records with missing unmet financial need, only those

students who completed a FAFSA would have an unmet need calculation on file within the

BANNER system. It is plausible that 24% of students did not complete the FAFSA, and did not

complete it in random fashion. It was therefore hypothesized that the data were Missing

Completely at Random (MCAR) (Rubin, 1976). Little's MCAR test was used to test this

hypothesis. Results from Little's MCAR Test (Little, 1988) via the *SPSS: Explore Missing

Values* function resulted in a chi-square= 1.779 (df= 2; p< .411). The researcher therefore failed

to reject the null hypothesis and concluded that the data was MCAR.

While data that are MCAR are not problematic in terms of their potential for biasing

results, they can produce issues with power as they reduce sample size and degrees of freedom

(Obsorne, 2015). SPSS, when confronted with missing data, defaults to complete case analysis

(i.e. cases with missing data are deleted from the analysis), resulting in reduced sample size. To

prevent potential issues with power, the researcher replaced the missing data utilizing the

Multiple Imputation-Impute Missing Data Values function within SPSS (Osborne, 2015; Allison,

2002; Cox et al, 2014). Imputation is a technique that utilizes regression modeling to predict

reasonable scores to replace missing values given other correlated variables (Osborne, 2015).

All variables (both dependent and independent) were included within the automatic imputation

method (Graham, 2009; Manly & Wells, 2014). Ten imputations were computed and imputed

values compared reasonably to observed values (Osborne, 2013). Table 1 displays the imputation

results for the variable high school GPA. Table 2 displays the imputation results for the variable unmet financial need.

Table 1. Imputation Results for High School GPA

Data	Imputation	N	Mean	Std. Deviation	Minimum	Maximum
Original Data		9154	2.5355	.51286	.0714	4.0000
Imputed Values	1	2049	2.5196	.52059	.7986	3.9928
	2	2049	2.5115	.49928	.8352	3.9236
	3	2049	2.5062	.50857	.3356	3.9213
	4	2049	2.5049	.50821	.8846	3.9488
	5	2049	2.4993	.52870	.1091	3.9643
	6	2049	2.5214	.50745	.9947	3.9969
	7	2049	2.5085	.52455	.5987	3.9975
	8	2049	2.5111	.52602	.3665	3.9920
	9	2049	2.5201	.51658	.9514	3.9821
	10	2049	2.4898	.51900	.9549	3.9278
Complete Data After Imputation	1	11203	2.5326	.51430	.0714	4.0000
	2	11203	2.5311	.51047	.0714	4.0000
	3	11203	2.5302	.51218	.0714	4.0000
	4	11203	2.5299	.51213	.0714	4.0000
	5	11203	2.5289	.51596	.0714	4.0000
	6	11203	2.5330	.51188	.0714	4.0000
	7	11203	2.5306	.51510	.0714	4.0000
	8	11203	2.5311	.51536	.0714	4.0000
	9	11203	2.5327	.51356	.0714	4.0000
	10	11203	2.5272	.51427	.0714	4.0000

Table 2. Imputation Results for Unmet Financial Need

Data	Imputation	N	Mean	Std. Deviation	Minimum	Maximum
Original Data		8517	9006.40	9139.444	-60587.21	155157.00
Imputed Values	1	2686	8863.20	9325.687	-20195.79	43059.44
	2	2686	9079.74	9026.899	-22632.00	43183.56
	3	2686	9104.92	9164.470	-19879.07	43871.26
	4	2686	9283.73	9273.503	-20182.80	37892.41
	5	2686	9153.63	9318.997	-21002.87	43347.06
	6	2686	9232.78	9344.542	-19218.25	40468.79
	7	2686	9392.47	8999.545	-19885.79	44765.81
	8	2686	8889.96	9147.513	-27520.62	36939.22
	9	2686	9624.61	9325.381	-20863.23	45831.14
	10	2686	9140.49	9198.087	-21164.18	39479.28
Complete Data After Imputation	1	11203	8972.06	9184.226	-60587.21	155157.00
	2	11203	9023.98	9112.240	-60587.21	155157.00
	3	11203	9030.02	9145.138	-60587.21	155157.00
	4	11203	9072.89	9172.113	-60587.21	155157.00
	5	11203	9041.70	9182.610	-60587.21	155157.00
	6	11203	9060.67	9189.124	-60587.21	155157.00
	7	11203	9098.96	9107.190	-60587.21	155157.00
	8	11203	8978.48	9141.106	-60587.21	155157.00
	9	11203	9154.62	9187.740	-60587.21	155157.00
	10	11203	9038.55	9153.306	-60587.21	155157.00

Following multiple imputation, three of the five continuous variables (high school GPA, unmet financial need, and college GPA) were converted to the standard normal distribution (z-scores). According to Osborne (2015), the transformation of continuous predictors to z-scores is a best practice because it aids in the interpretation of individual variable results and in the comparison across variables. Prior to conversion to z-scores, high school GPA and college GPA were recorded to the hundredths (ex: 1.25) and unmet financial need was recorded to the whole dollar (ex: $9,504). Without conversion to z-scores, interpretation of the odds ratios for these

variables would have been difficult as each incremental change (in hundredths in the case of GPA and in dollars in the case of unmet financial need)would have been interpreted as an increase in the odds of the outcome occurring. Converting to z-scores allows for the interpretation of the odds based upon an increase in one standard deviation (Osborne, 2015). The other continuous variables (age and extent of remedial math need) were recorded to the whole number, making interpretation of the odds ration much easier. For example, age ranged from 16-74 and extent of remedial math need ranged from 1-17. They were therefore not converted to z-scores and remained in their original state.

Coding Schemes

All nominal covariates (full-time/part-time status, race, gender) were dummy coded, which is the traditional method for dealing with nominal level variables within regression analysis (Osborne, 2015). Race was collapsed into a single variable (White or Non-White) due the low number of other races (especially Hispanic and Asian) within the populations, especially the populations for models 2-4. Without collapsing the race category, the researcher would not have had enough cases within each race category to yield a reliable model. Table 3 details all of the covariates that were used within the study, their type, and any recoding that was used.

Table 3. Coding Scheme for Covariates

Variable Name	Variable Type	Coding
Age	Continuous	
Enrolled Full Time* in First Term	Categorical	1, Yes 0, Part-time
High school GPA	Continuous	
White	Categorical	1, Yes 0, Non-white
Sex	Categorical	1, Female 0, Male
Extent of remedial math need	Continuous	
Unmet financial need	Continuous	
College GPA	Continuous	

Full time= 12 or more credit hours

In addition, all outcome variables were dummy coded. Table 4 details all of the outcome variables used within the study, their type, and their dummy coding scheme.

Table 4. Coding Scheme for Outcomes

Variable Name	Variable Type	Coding
Enrollment in remedial math course	Categorical	1, Yes 0, No
Completion of remedial math sequence	Categorical	1, Yes 0, No
Enrollment in college-level math course	Categorical	1, Yes 0, No
Successful completion of college-level math course	Categorical	1, Yes 0, No

Research Design

Multiple logistic regression analysis was the statistical technique utilized in this study. This statistical technique was chosen because all four outcome variables (enrollment in a remedial math course, completion of the remedial math sequence, enrollment in a college-level math course, and passing a college-level math course) were dichotomous. While other methods exist for exploring dichotomous outcomes, such as the linear probability model and discriminate function analysis, they can result in probabilities that exceed the 0.00 to 1.00 range and residuals that are highly heteroscedastic and not normally distributed (Osborne, 2015). Logistic regression is therefore "currently considered the best practice when dealing with outcomes that are dichotomous or categorical in nature" (Osborne, 2015, p. 17).

This study sought to understand if age is indeed a research-worthy variable within the remedial education research base, as posited by some researchers (Adelman, 2005; Choy, 2002a). The study therefore asked, is age a significant predictor of: enrollment in a remedial

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math course; completion of the remedial math sequence; enrollment in a college-level math course; and completion, with a grade of C or better, of a college-level math course? While understanding the effect that age has on remedial outcomes is important, other pre-college entry variables (such as high school GPA, ethnicity/race, gender, and full-time vs. part-time status) may also play a role in whether or not students successfully remediate. The study therefore also sought to understand what other pre-college variables help to predict successful remediation. Finally, while understanding the effect pre-college entry variables have on remedial outcomes is important, postsecondary practitioners have little control over the cumulative effects of secondary schooling, race, ethnicity, or the age at which students decide to enroll in postsecondary coursework. This study therefore included two additional post-college entry variables, cumulative college GPA and unmet financial need; both of which can be influenced by postsecondary policies and practices. The other research question thus asked what are the most significant pre- and post-college entry predictors of enrollment in a remedial math course; completion of the remedial math sequence; enrollment in a college-level math course; and completion, with a grade of C or better, of a college-level math course?

To answer these questions, a series of four (corresponding with the four outcome variables) multiple logistic regression main effects models were computed, containing both the pre-college and post-college entry variables. All independent variables were entered into each model through simultaneous/forced entry. Osborne (2015) states that when analysis is grounded in theory forced entry is "one of the most common and most accepted methods of entry" (p. 249). Figure 3 illustrates the conceptual framework for each model.

Figure 3. Conceptual Framework for Logistic Regression Models
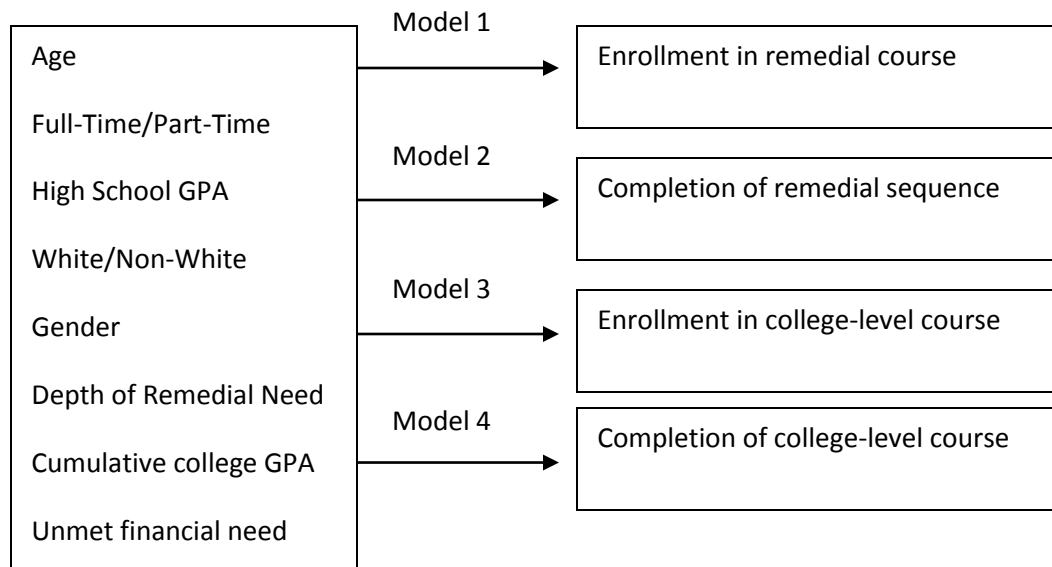
Testing of Assumptions

Because logistic regression is a nonparametric technique, the typical assumptions of regression, such as normality and homoscedasticity are not required (Field, 2013). According to Field (2013), the following assumptions should be met within any logistic regression analysis: absence of collinearity, a fully represented data matrix, absence of influential cases, and a linear relationship between continuous variables and the logit of the outcome variable.

Highly correlated independent variables can result in extremely large standard errors and should therefore be detected and dealt with before running any regression analyses (Osborne, 2015). To inspect for potential collinearity issues, correlations were computed for each model to measure the pairwise correlation between pairs of independent variables while controlling for the effect of other variables. The results were examined for possible collinearity issues. Results indicated that no pair of variables had correlations above the .900 threshold (Hair et al, 2006; Osborne, 2015). Therefore, there was no concern with collinearity and all independent variables

were retained for inclusion in the logistic regression models. All four correlation matrixes are included in the appendix (APPENDIX C).

Not having a fully represented data matrix due to sparse data can be problematic to the logistic regression computation. Unless enough data exists for all combinations of variables (i.e., a fully represented data matrix exists) the logistic regression computation has difficulty computing the odds of a given outcome because the goodness-of-fit tests produced in SPSS assume that the expected frequencies for each variable are greater than 1 and that no more than 20% are less than 5 (Field, 2013). To detect any issues related to sparse data, contingency tables were produced. The only variable for which sparseness was identified as a potential issue was race. The race codes were therefore collapsed into one nominal variable: White or Non-white (Osborne, 2015).

Highly influential cases are those cases which exert a disproportionate influence on the overall outcome. According to Osborne (2015) "each case should contribute relatively equally to overall model fit /lack of fit" (p. 104). To test for any potentially influential cases, Cook's Distances were computed for each population and frequencies were run (Field, 2013). Cook's Distance determines how much the residuals of all cases would change if a specific case were removed from the analysis (Osborne, 2015). Cases with a Cook's Distance of 1 or greater are considered to be unduly influential and therefore candidates for further inspection and possible deletion (Field, 2013). For each of the four models, Cooks Distances were calculated. In Model 1 the Cook's Distance analogue ranged from .00004 to .22146, with the 95th percentile at .00486. In Model 2, the Cook's Distance analogue ranged from .00001 to .38578, with the 95th percentile at .02310. For Model 3, the Cook's Distance analogue ranged from .00258 to .17926, with the 95th percentile at .04058. Lastly, in Model 4, the Cook's Distance analogue ranged from .00501

to .47639, with the 95th percentile at .06540. It was therefore assumed that there were no potentially influential cases and all cases were retained in each of the four models (Field, 2013).

To test the assumption that all continuous variables within each model (age, high school GPA, extend of remedial math need, cumulative college GPA, and unmet financial need) are linearly related to the log of each of the four outcome variables, logistic regressions were run that included predictors that are the interaction between each predictor and the log of itself (Hosmer & Lemeshow, 1989). Two of the models (Model 1 and Model 2) had interaction terms that were significant and where therefore assumed to have violated the assumption of linearity on the logit (Field, 2013). In Model 1, college GPA was assumed to not be linearly related to the logit of the outcome variable (enrollment in a remedial course), Wald= 29.338, df= 1, p < .001, as was age, Wald= 5.276, df= 1, p < .05. In Model 2, the extent of remedial math need was assumed to not be linearly related to the logit of the outcome variable (completion of the remedial sequence), Wald= 6.583, df= 1, p < .05, as was college GPA, Wald= 4.123, df= 1, p < .05.

Synthesis

At the conclusion of data collection, data set construction, data cleaning, and data transformation, the analytic data set consisted of 11, 203 student records. Each student record consisted of eight predictor (independent) variables: age; full-time/part-time status; high school GPA; white/non-white; gender; depth of remedial need; college GPA; and unmet financial need. Age, high school GPA, depth of remedial need, college GPA, and unmet financial need were continuous variables, with high school GPA, college GPA and unmet financial need converted to z-scores. Full-time/part-time status, white/non-white, and gender were dichotomous (categorical) variables. Each student record also had four outcome (dependent) dichotomous variables: enrollment in a remedial math course; completion of the remedial math sequence; enrollment in a

college-level math course; and completion (with a grade of C or better) of a college-level math course.

CHAPTER 4: RESULTS

Following data collection, data set construction, data cleaning, data transformation, and the testing of assumptions, as outlined in Chapter 3, the researcher computed descriptive statistics for the populations of each logistic regression model. Multiple iterations of descriptive statistics were computed because the study population changed (decreased) with each successive model as students failed to progress onto the next stage of the remediation process. Following inspection of descriptive statistics, the researcher computed four multiple logistic regression main effects models containing both the pre-college and post-college entry variables. An analysis of overall model fit, Nagelkerke R-Squared, chi-squared, beta coefficients, and p values $\leq .05$ was conducted for each model (Field, 2013). All independent variables were entered into each model through simultaneous/forced entry (Osborne, 2015).

The first model examined the conditional probability of enrolling in a remedial math course following referral to remedial math education. The second model examined the conditional probability of completing the remedial math sequence following enrollment in a remedial math course. The third model examined the conditional probability of enrolling in a college-level math course following completion of the remedial math sequence. The fourth and final model examined the conditional probability of passing a college-level math course with a grade of C or better. Because each successive model contained a smaller and smaller number of students, power analyses were conducted and reported for each model (Osborne, 2015). This chapter will focus upon the analysis of descriptive statistics and the analysis of each logistic regression model.

Descriptive Statistics

This study focused upon the process of remediation, from referral to remedial coursework to passing the college-level course, in an effort to explore the major explanatory variables that

predict attrition at each step within the process. Because of this, each logistic regression model contained a different (smaller) population of students as students failed to progress within the remedial process. The original analytic data set consisted of 11,203 student records. The data set included all first-time associate degree-seeking students referred to remedial math coursework (based upon their ACT or COMPASS test scores) during the fall 2013 and fall 2014 semesters across the ten community colleges included in the study. Of this population, 11.8% (n= 1,330) attempted a remedial math course during the two academic years covered in the study. The second analytic data set, consisting of all students from the original data set that attempted a remedial math course, contained a total population of 1,330 students. Of this population, 46.9% (n= 625) completed the remedial math sequence (received a grade of C or better, or Pass, in the highest remedial math course offered at that institution) during the two academic years covered in the study. The third analytic data set, consisting of all students from the second data set that completed the remedial math sequence, contained a total population of 625 students. Of this population, 60.8% (n=380) enrolled in a college-level math course during the two academic years covered in the study. The fourth and final analytic data set, consisting of all students from the third data set that enrolled in a college-level math course, contained a total population of 380 students. Of this population, 54.2% (n=206) passed (with a grade of C or better) a college-level math course during the two academic years covered in the study. This population of successfully remediated students represents 1.8% of the initial population of 11,203 students referred to remedial math. Table 5 displays the frequency and percentage of each population that progressed onto the next stage of the remedial process.

Table 5. Frequency and Percentage of Progression through the Remedial Process

	N	Percent that Progressed to Next Stage
First Population	11,203	11.8%
Second Population	1,330	46.9%
Third Population	625	60.8%
Fourth Population	380	54.2%
Successfully Remediated	206	---

Descriptive Statistics across all Populations

Six pre-college variables (gender, race, full-time/part-time status during first semester of college enrollment, age, high school GPA, and extent of remedial math need) and two post-college entry variables (college GPA and total dollar amount of unmet financial need) were collected or imputed (in the case of high school GPA and unmet financial need) for each student in the study. For each of the four populations, as well as for the population of students that successfully remediated (passed a college-level math class with a grade of C or better), descriptive statistics were calculated and reported.

Gender. Females comprised the majority (57.2%) of students referred to remedial math and they maintained a majority across all of the populations (ranging from 57.2% to 64.1%). With each step in the remedial process, the populations became more female, with 64.1% of those who successfully remediated being female. Overall, approximately 2% of females (132 out of 6,410) and 1.5% of males (74 out of 4,793) referred to remediation successfully remediated.

Table 6 shows the frequency and percentage of gender across all four of the study populations and among those who successfully remediated.

Table 6. Frequency and Percentage of Gender across all Populations

	Population 1 (N= 11,203) Referred to remedial math *N (%)*	Population 2 (N= 1,330) Enrolled in remedial math course *N (%)*	Population 3 (N= 625) Completed remedial sequence *N (%)*	Population 4 (N= 380) Enrolled in college-level math *N (%)*	Successfully Remediated (N= 206) *N (%)*
Female	6,410 (57.2%)	790 (59.4%)	384 (61.4%)	235 (61.8%)	132 (64.1%)
Male	4,793 (42.8%)	540 (40.6%)	241 (38.6%)	145 (38.2%)	74 (35.9%)

Race. Although race was collapsed into a single variable (White or Non-White) in the final logistic regression analyses, descriptive statistics were computed for all race categories. No single race had a majority among the populations, although overall the populations became less Black (declining from 44.6% to 36.4%) and less Asian (declining 1.2% to 1.0%) from referral to successful remediation. Among those referred to remediation, 44.6% were Black, 42.1% were White, 7.5% were part of the "Other" category (Unknown, American Indian or Alaskan Native, Native Hawaiian/Other Pacific Islander, Multiple Races), 4.6% were Hispanic, and 1.2% were Asian. In terms of successful remediation, approximately 2% (95 out of 4,722) of Whites, 1.4% of Blacks (75 out of 5,006), 2.2% of Hispanics (12 out of 524), 1.9% of Asians (2 out of 104), and 2.5% of students in the Other category (22 out of 847) made a C or better in a college-level math class. Table 7 shows the frequency and percentage of race across all four of the study populations and among those who successfully remediated.

Table 7. Frequency and Percentage of Race across all Populations

	Population 1 (N= 11,203) Referred to remedial math N (%)	Population 2 (N= 1,330) Enrolled in remedial math course N (%)	Population 3 (N= 625) Completed remedial sequence N (%)	Population 4 (N= 380) Enrolled in college-level math N (%)	Successfully Remediated (N= 206) N (%)
White	4,722 (42.1%)	529 (39.7%)	278 (44.4%)	168 (44.2%)	95 (46.1%)
Black	5,006 (44.6%)	630 (47.3%)	260 (41.6%)	150 (39.4%)	75 (36.4%)
Hispanic	524 (4.6%)	68 (5.1%)	33 (5.2%)	25 (6.5%)	12 (5.8%)
Asian	104 (1.2%)	8 (.06%)	6 (.96%)	2 (.05%)	2 (1.0%)
Other*	847 (7.5%)	95 (7.1%)	48 (7.6%)	35 (9.2%)	22 (10.6%)

The category "other" was comprised of the following: Unknown, American Indian or Alaskan Native, Native Hawaiian/Other Pacific Islander, Multiple Races

As stated above, race was collapsed into a single variable (White or Non-White) in the final logistic regression analyses. Non-White comprised the majority across each of the populations, but, for the most part, the populations became more White with each step in the remedial process. Among those referred to remedial math coursework (Population 1), 42.1% were White and 57.9% were Non-White. Among those who enrolled in a remedial math course (Population 2), 39.7% were White and 60.3% were Non-White. Population 3 (those who completed the remedial math sequence) was made up of 44.4% White and 55.6% Non-White. Among those who enrolled in a college-level math course (Population 4), 44.2% were White and 55.8% were Non-White. Lastly, among those who successfully remediated, 46.1% were White and 53.9% were Non-White.

Full-time enrollment. Consistently, through each step in the remedial process, those who had enrolled on a full-time basis ($\geq$ 12 credit hours) during their first semester of college maintained the majority (ranging from 69.4% to 78.2%). Approximately 2% (159 out of 7,778) of those who enrolled full-time during their first semester successfully remediated, compared to 1.3% (47 out of 3,425) of those who enrolled part-time. Table 8 shows the frequency and percentage of full-time/part-time status across all four of the study populations and among those who successfully remediated. The proportion of full-time enrollment for White and Non-White and for male and female students was calculated. No significant differences were observed between Whites and Non-Whites and between males and females.

Table 8. Frequency and Percentage of Full-Time & Part-Time Enrollment across all Populations

	Population 1 (N= 11,203) Referred to remedial math *N (%)*	Population 2 (N= 1,330) Enrolled in remedial math course *N (%)*	Population 3 (N= 625) Completed remedial sequence *N (%)*	Population 4 (N= 380) Enrolled in college-level math *N (%)*	Successfully Remediated (N= 206) *N (%)*
Full-time*	7,778 (69.4%)	1,022 (76.8%)	489 (78.2%)	296 (77.9%)	159 (77.2%)
Part-time	3,425 (30.6%)	308 (23.1%)	136 (21.8%)	84 (22.1%)	47 (22.8%)

Full-time equals $\geq$ 12 credit hours

Age. The average age of the populations remained fairly consistent across each step in the remedial process, ranging from a high of 20.4 to a low of 19.8. Within the second population (students who enrolled in a remedial course), the average age was slightly lower (19.8) than the average age in any of the other populations. The age range narrowed slightly from the first to third steps in the process. Among those referred to remediation, age ranged from 16-74. Among those who enrolled in a remedial math course, age ranged from 16-61. The remaining three

populations (remedial sequence completers, those who enrolled in a college-level math course, and those who successfully remediated), had an age range of 16-51. Table 9 shows the mean, standard deviation and range of age across all four of the study populations and among those who successfully remediated.

Table 9. Mean, Standard Deviation, and Range of Age across all Populations

	Population 1 (N= 11,203) Referred to remedial math	Population 2 (N= 1,330) Enrolled in remedial math course	Population 3 (N= 625) Completed remedial sequence	Population 4 (N= 380) Enrolled in college-level math	Successfully Remediated (N= 206)
Mean	20.4	19.8	20.0	20.0	20.2
Standard Deviation	4.791	3.985	4.403	4.450	4.832
Range	16-74	16-61	16-51	16-51	16-51

Many higher education researchers divide the student population into adult (≥ 25 years) and traditional-age (≤ 24 years) (Ashar & Skenes, 1993; Naretto, 1995; Braxton & Brier, 1989; Benshoff, 1991; Donaldson & Graham, 1999). While this study utilized age as a continuous variable within each of the logistic regression models, the frequency and percentage of adult and traditional-age students was also computed across each of the populations. Traditional-age students comprised 90.2% of the students referred to remedial math coursework. Across all four of the study populations, and amongst those who successfully remediated, traditional-age students maintained the overwhelming majority (ranging from 90.2% to 93.5%). Among adult students, 1.7% (19 out of 1,099) successfully remediated, compared with 1.8% (187 out of 10,104) of traditional-age students. Table 10 shows the frequency and percentage of adult and

traditional-age students across all four of the study populations and among those who

successfully remediated.

Table 10. Frequency and Percentage of Adult & Traditional-Age Students across all Populations

	Population 1 (N= 11,203) Referred to remedial math *N (%)*	Population 2 (N= 1,330) Enrolled in remedial math course *N (%)*	Population 3 (N= 625) Completed remedial sequence *N (%)*	Population 4 (N= 380) Enrolled in college-level math *N (%)*	Successfully Remediated (N= 206) *N (%)*
Adult	1,099 (9.8%)	87 (6.5%)	48 (7.7%)	30 (7.9%)	19 (9.2%)
Traditional-Age	10,104 (90.2%)	1,243 (93.5%)	577 (92.3%)	350 (92.1%)	187(90.8%)

High school GPA. With each step in the remedial process, the average high school GPA

of the populations increased, with the initial population having an average of 2.52 and the

remediated population having an average of 2.64. Table 11 shows the mean, standard deviation

and range of high school GPA across all four of the study populations and among those who

successfully remediated.

Table 11. Mean, Standard Deviation, and Range of High School GPA across all Populations

	Population 1 (N= 11,203) Referred to remedial math	Population 2 (N= 1,330) Enrolled in remedial math course	Population 3 (N= 625) Completed remedial sequence	Population 4 (N= 380) Enrolled in college-level math	Successfully Remediated (N= 206)
Mean	2.52	2.50	2.59	2.61	2.64
Standard Deviation	.5142	.4773	.5006	.4923	.4760
Range	1.00-4.00	1.00-3.94	1.00-3.86	1.00-3.86	1.29-3.80

Because high school GPA was found to be a significant predictor of remedial education success within some of the logistic regression analyses, the researcher conducted independent samples t-tests to better understand the differences in high school GPA across various demographic groups. Independent samples t-tests were conducted to determine whether or not there was a statistically significant difference in average high school GPA between Whites and Non-Whites, and between males and females within each study population and among those who successfully remediated. Within Population 1 (all students referred to remedial math education), there was a statistically significant difference in mean high school GPA for Whites (M= 2.59, SD= .5204) and Non-Whites (M= 2.47, SD= .5042); t= 11.75, p= .000. In addition, there was a statistically significant difference in mean high school GPA for females (M= 2.59, SD= .5109) and males (M= 2.43, SD= .5033); t= 17.07, p= .000. Within Population 2 (those who enrolled in a remedial math course), there was a statistically significant difference in mean high school GPA for Whites (M= 2.56, SD= .4541) and Non-Whites (M= 2.46, SD= .4883); t= 3.67, p= .000, and for females (M= 2.57, SD= .4739) and males (M= 2.41, SD= .4666); t= 6.01, p= .000. For the

latter two populations (those who completed the remedial sequence and those who enrolled in a college-level math course) there was no statistically significant difference in mean high school GPA for Whites and Non-Whites. In other words, by this phase within the remedial process, Whites and Non-Whites were fairly homogenous in terms of high school GPA. The statistically significant differences between genders, however, remained. Within Population 3 (those who completed the remedial sequence), there was a statistically significant difference in mean high school GPA for females (M= 2.65, SD= .5084) and males (M= 2.50, SD= .4748); t= 3.67, p= .000. Likewise, in Population 4 (those who enrolled in a college-level math course), there was a statistically significant difference in mean high school GPA for females (M= 2.67, SD= .4894) and males (M= 2.51, SD= .4830); t= 3.06, p= .002. Among those who successfully remediated (passed a college-level math course with a grade of C or better), there was a statistically significant difference in mean high school GPA for Whites (M= 2.71, SD= .4849) and Non-Whites (M= 2.58, SD= .4613); t= 2.05, p= .042, but no significant difference between females and males.

Extent of remedial need. The numeric distance between a student's ACT score and the cut score required to avoid remediation (19) ranged from 1-17 among the population referred to remediation. The range narrowed however with each step in the remedial process. Among those who enrolled in a remedial course, the remedial need ranged from 1-10. Among those who completed the remedial sequence and those who enrolled in a college-level math course, the remedial need ranged from 1-8. Finally, among those who successfully remediated, the remedial need ranged from 1-7. The average fluctuated slightly across populations, ranging from 2.46 to 3.00, and had no discernable pattern. Table 12 shows the mean, standard deviation and range of

remedial math need across all four of the study populations and among those who successfully remediated.

Table 12. Mean, Standard Deviation, and Range of Remedial Math Need across all Populations

	Population 1 (N= 11,203) Referred to remedial math	Population 2 (N= 1,330) Enrolled in remedial math course	Population 3 (N= 625) Completed remedial sequence	Population 4 (N= 380) Enrolled in college-level math	Successfully Remediated (N= 206)
Mean	2.97	3.00	2.64	2.50	2.46
Standard Deviation	1.294	1.240	1.196	1.163	1.137
Range	1-17	1-10	1-8	1-8	1-7

In addition, the researcher conducted independents samples t-tests to examine significant differences in remedial need across race and gender within each study population and among those who successfully remediated. Across all four study populations and among those who successfully remediated, statistically significant differences in remedial need existed between Whites and Non-Whites. Significant differences between females and males were found only among those referred to remediation (Population 1) and those who successfully completed the remedial sequence (Population 3). Within Population 1 (all students referred to remedial math education), there was a statistically significant difference in extent of remedial need for Whites (M= 2.72, SD= 1.233) and Non-Whites (M= 3.15, SD= 1.307); t= -17.44, p= .000, as well as for females (M= 3.02, SD= 1.290) and males (M= 2.90, SD= 1.295); t= 4.99, p= .000. Within Population 2 (those who enrolled in a remedial math course), there was a statistically significant

difference in extent of remedial need for Whites (M= 2.78, SD= 1.146) and Non-Whites (M= 3.14, SD= 1.279); t= -5.22, p= .000, but no statistically significant differences for females and males. Within Population 3 (those who completed the remedial math sequence), there was a statistically significant difference in extent of remedial need for Whites (M= 2.47, SD= 1.110) and Non-Whites (M= 2.77, SD= 1.246); t= -3.15, p= .002, as well for females (M=2.71, SD= 1.214) and males (M= 2.52, SD= 1.159); t= 1.99, p= .047. Within Population 4, there was a statistically significant difference in extent of remedial need for Whites (M= 2.27, SD= .977) and Non-Whites (M= 2.68, SD= 1.265); t= -3.57, p= .000, but no for females and males. Lastly, among those who successfully remediated (passed a college-level math course with a grade of C or better), there was a statistically significant difference in extent of remedial need for Whites (M= 2.22, SD= 1.002) and Non-Whites (M= 2.66, SD= 1.210); t= -2.79, p= .006, but no significant difference between females and males.

College GPA. Among those who were referred to remedial math, the average college GPA was 1.86. Among those who successfully remediated, the average was 2.34. With each step in the remedial process, the average college GPA increased, with one exception. Among students who attempted a college-level math class, the average college GPA dropped from 2.20 (among those who completed the remedial sequence) to 2.17. Table 13 shows the mean, standard deviation and range of college GPA across all four of the study populations and among those who successfully remediated.

Table 13. Mean, Standard Deviation, and Range of College GPA across all Populations

	Population 1 (N= 11,203) Referred to remedial math	Population 2 (N= 1,330) Enrolled in remedial math course	Population 3 (N= 625) Completed remedial sequence	Population 4 (N= 380) Enrolled in college-level math	Successfully Remediated (N= 206)
Mean	1.86	1.89	2.20	2.17	2.34
Standard Deviation	1.198	.9773	.8903	.9042	.8365
Range	0.00-4.00	0.00-4.00	0.00-4.00	0.00-4.00	0.00-4.00

Again, the researcher attempted to decipher significant differences in GPA across race and gender within each study population and among those who successfully remediated. Across all four study populations and among those who successfully remediated, statistically significant differences in college GPA existed between females and males. Significant differences between Whites and Non-Whites were found only among those referred to remediation (Population 1), among those who enrolled in a remedial math course (Population 2), and among those who completed the remedial math sequence (Population 3). In the latter stages of the remedial process (enrollment and completion with a grade of C or better in a college-level math course), Whites and Non-whites were homogenous in terms of college GPA. Within Population 1 (all students referred to remedial math education), there was a statistically significant difference in college GPA for Whites (M= 2.06, SD= 1.200) and Non-Whites (M= 1.71, SD= 1.170); t= 15.77, p= .000, as well as for females (M= 1.90, SD= 1.202) and males (M= 1.79, SD= 1.189); t= 4.69, p= .000. Within Population 2 (those who enrolled in a remedial

math course), there was a statistically significant difference in college GPA for Whites (M= 2.04, SD= .9804) and Non-Whites (M= 1.80, SD= .9635); t= 4.522, p= .000, as well as for females (M= 1.99, SD= .9770) and males (M= 1.76, SD= .9625); t= 4.24, p= .000.Within Population 3 (those who completed the remedial math sequence), there was a statistically significant difference in college GPA for Whites (M= 2.30, SD= .8709) and Non-Whites (M= 2.13, SD= .8998); t= 2.36, p= .019, as well for females (M=2.32, SD= .8533) and males (M= 2.02, SD= .9179); t= 4.19, p= .000.Within Population 4 (those who enrolled in a college-level math course), there was a statistically significant difference for females (M=2.28, SD= .8664) and males (M= 1.98, SD= .9344); t= 3.26, p= .001.Lastly, among those who successfully remediated (passed a college-level math course with a grade of C or better) there a statistically significant difference for females (M=2.43, SD= .8121) and males (M= 2.17, SD= .8588); t= 2.17, p= .031.

Unmet financial need. Among those referred to remedial math, the total amount of unmet financial need ranged from -$60,587 to $155,157.Across the remaining populations, unmet financial need ranged from -$11,627 to $155,157 (among those who enrolled in a remedial course), from -$10,896 to $142,592 (among those who completed the remedial sequence), -$10,201 to $68,765 (among those who enrolled in a college-level math course), and -$5,899 to $68,765 (among those who successfully remediated). Negative unmet financial need indicates that a student was over-awarded aid. Title IV funds (loans and grants backed by the federal government) cannot exceed the total cost of attendance. However, some institutions or private donors award scholarships, periodically resulting in negative unmet financial need. In addition, some programs at the ten colleges included in the study have annual tuition and fee rates far in excess of other programs. For example, the Aviation Program at one college, which trains helicopter pilots and mechanics, has an annual tuition and fee rate of $50,000. Nursing

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programs also have higher tuition and fee rates, some in the $15,000 to $20,000 range, when lab

fees, books, and licensing exam preparation and fees are taken into account. It is also important

to note that a high unmet financial need could also indicate that a student has a very low

expected family contribution (EFC). A low EFC means that the student's income, relative to his

or her daily living expenses and number of dependents, is unlikely to cover a large percentage of

the student's total cost of attendance (tuition, fees, books, transportation, rent, etc.). The average

unmet need fluctuated across populations, ranging from $8,623 to $9,210, and had no

discernable pattern. Table 14 shows the mean, standard deviation and range of unmet financial

need across all four of the study populations and among those who successfully remediated.

Table 14. Mean, Standard Deviation, and Range of Unmet Financial Need across all Populations

	Population 1 (N= 11,203) Referred to remedial math	Population 2 (N= 1,330) Enrolled in remedial math course	Population 3 (N= 625) Completed remedial sequence	Population 4 (N= 380) Enrolled in college-level math	Successfully Remediated (N= 206)
Mean	$9,038	$8,623	$9,147	$8,683	$9,210
Standard Deviation	$9,153	$9,984	$10,207	$8,258	$8,850
Range	-$60,587 - $155,157	-$11,627 - $155,157	-$10,896- $142,592	-$10,201 - $68,765	-$5,899 - $68,765

Logistic Regression Analyses

Following an analysis of descriptive statistics for each of the four study populations, the

researcher analyzed the four logistic regression main effects models. Overall model fit,

Nagelkerke R-Squared, chi-squared, beta coefficients, and p values ≤ .05 were reported and

analyzed for each model (Field, 2013). The following section will cover the results for each of the four models.

Model 1: The Conditional Probability of Enrolling in a Remedial Math Course

Model 1 explored the conditional probability of enrolling in a remedial math course among the 11,203 students referred to remedial math education (based upon their ACT or COMPASS test scores) during the fall 2013 and fall 2014 semesters. A multiple logistic regression main effects analysis was conducted to predict enrollment in a remedial math course using age, race, gender, high school GPA, extent of remedial math need, full-time/part-time status during the first semester of enrollment, unmet financial need, and college GPA as predictors. Of the 11,203 students referred to remedial math, 1,330 (11.6%) attempted a remedial math course during the two academic years following initial enrollment.

A test of the full model against a constant only model was statistically significant, indicating that the predictors as a set reliably distinguished between those who enrolled in a remedial math course and those who did not (chi square= 82.449, $p < .001$ with df= 8). Nagelkerke's R-square of .014 indicated an overall weak relationship between prediction and grouping. Prediction success overall was 88.1% (0% for enrollment and 100% for non-enrollment), which was identical to the null model. In other words, Model 1 was no better at predicting enrollment in a remedial math course than was the null model. This is likely due to the high percentage (88%) of students who did not enroll in a remedial math course. Table 15 includes the Model Summary.

Table 15. Model Summary for Model 1

	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
Step 1	8081.475ª	.007	.014

The Wald criterion demonstrated that five of the variables made a significant contribution to prediction: age (p=.000), full-time enrollment (p=.000), gender (p=.032), high school GPA (p=.001) and college GPA (p=.020). None of the other variables (race, remedial math need, and unmet financial need) were significant predictors. Table 16 shows the variables included in the model and their relative contribution to prediction.

Table 16. Variables in the Equation for Model 1

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1ª	AGE	-.036	.008	20.377	1	.000	.964
	FULLTIME	-.406	.070	34.112	1	.000	.666
	WHITE	.85	.061	1.918	1	.166	1.089
	GENDER	-.130	.061	4.593	1	.032	.878
	REMEDIAL NEED	.303	.023	1.628	1	.202	1.030
	HS GPA	-.111	.032	11.769	1	.001	.895
	COLLEGE GPA	.076	.033	5.421	1	.020	1.079
	UNMET NEED	-.032	.031	1.043	1	.307	.969

CONSTANT	-1.247	.175	50.517	1	.000	.287

The exponential beta coefficient (Exp(B)) value for the variable AGE indicated that when age increases by one unit, the odds ratio is .964 less. Therefore, with each one year increase in age, a student is .964 times less likely to enroll in a remedial math course. For example, a 19 year old student is .964 times as likely as an 18 year old student to enroll in a remedial math course, whereas a 25 year old student is .802 times as likely. The Exp(B) value for the variable FULLTIME indicated that when a student is enrolled full-time during the first semester of college, the odds ratio is .666 less. Therefore, students who enroll full-time ($\geq$12 credit hours) during the first semester of college are .666 times less likely to enroll in a remedial math course than are students who enroll part-time ($\leq$ 12 credit hours). The Exp(B) value for the variable GENDER indicated that females were .878 times less likely to enroll in a remedial math course than male students. The Exp(B) value for the variable HS GPA indicated that when high school GPA increases by one standard deviation (.5142), the odds ratio is .895 times less. For example, a student with a high school GPA of 3.03 is approximately .895 times less likely to enroll in a remedial math course than a student with a high school GPA of 2.52. Lastly, the Exp(B) value for the variable COLLEGE GPA indicated that when college GPA increases by one standard deviation (1.198), the odds ratio is 1.079 times as large. For example, a student with a college GPA of 3.05 is 1.079 times more likely to enroll in a remedial math course than a student with a college GPA of 1.86.

Model 2: The Conditional Probability of Completing the Remedial Math Sequence

Model 2 explored the conditional probability of completing the remedial math sequence among the 1,330 students who enrolled in a remedial math course. A multiple logistic regression

main effects analysis was conducted to predict completion of the remedial math sequence using age, race, gender, high school GPA, extent of remedial math need, full-time/part-time status during the first semester of enrollment, unmet financial need, and college GPA as predictors. Of the 1,330 students who enrolled in a remedial math course, 625 (46.9%) completed the remedial math sequence during the two academic years following initial enrollment.

A test of the full model against a constant only model was statistically significant, indicating that the predictors as a set reliably distinguished between those who completed the remedial math sequence and those who did not (chi square= 253.737, p < .001 with df= 8). Nagelkerke's R-square of .232 indicated an overall moderate relationship between prediction and grouping. Prediction success overall was 68.7% (64.5% for sequence completion and 72.5% for non-completion), which was higher than the null model prediction success rate of 53.0%. Table 17 includes the Model Summary.

Table 17. Model Summary for Model 2

	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
Step 1	1585.220[a]	.174	.232

The Wald criterion demonstrated that five of the variables made a significant contribution to prediction: age (p=.001), remedial math need (p=.000), high school GPA (p=.012), unmet financial need (p=.029) and college GPA (p=.000). None of the other variables (full-time enrollment, race, gender) were significant predictors. Table 18 shows the variables included in the model and their relative contribution to prediction.

Table 18. Variables in the Equation for Model 2

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	AGE	.052	.016	10.675	1	.001	1.054
	FULLTIME	.034	.147	.053	1	.817	1.034
	WHITE	-.069	.126	.305	1	.581	.933
	GENDER	.001	.127	.000	1	.991	1.001
	REMEDIAL NEED	-.539	.055	95.465	1	.000	.583
	HS GPA	.168	.066	6.363	1	.012	1.182
	COLLEGE GPA	.626	.068	83.793	1	.000	1.870
	UNMET NEED	.135	.062	4.788	1	.029	1.144
	CONSTANT	.457	.346	1.741	1	.187	1.579

The Exp(B) value for the variable AGE indicated that when age increases by one unit, the odds ratio is 1.054 more. Therefore, with each one year increase in age, a student is 1.054 times more likely to complete the remedial math sequence. For example, a 19 year old student is 1.054 times as likely as an18 year old student to complete the remedial math sequence, whereas a 25 year old student is 1.371 times as likely. The Exp(B) value for the variable REMEDIAL NEED indicated that with each one unit increase in remedial need, completion of the remedial sequence was .583 times less likely. For example, a student with an 18 math ACT sub-score is .583 times as likely as a student with a 19 sub-score to complete the remedial math sequence. Likewise, a

student with a 15 sub-score is .115 times as likely as a student with a 19 sub-score to complete the remedial math sequence. In other words, the higher the remedial need (or the farther away from the cut score of 19), the less likely the student is to complete the remedial sequence. The Exp(B) value for the variable HS GPA indicated that when high school GPA increases by one standard deviation (.4773) , the odds ratio is 1.182 times more. For example, a student with a high school GPA of 2.98 is 1.182 times more likely to complete the remedial math sequence than a student with a high school GPA of 2.50. The Exp(B) value for the variable COLLEGE GPA indicated that when college GPA increases by one standard deviation (.97739), the odds ratio is approximately 1.870greater. For example, a student with a college GPA of 2.86 is 1.870 times more likely to complete the remedial math sequence than a student with a college GPA of 1.89. Lastly, the Exp(B) value for the variable UNMET NEED indicated that when unmet need increases by one standard deviation ($9,984), the odds ratio is approximately 1.144 greater. For example, a student with an unmet need of $18,607 is 1.144 times more likely to complete the remedial math sequence than a student with an unmet need of $8,623.

Model 3: The Conditional Probability of Enrolling in a College-Level Math Course

Model 3 explored the conditional probability of enrolling in a college-level math course among the 625 students who completed the remedial math sequence. A multiple logistic regression main effects analysis was conducted to predict enrollment in a college-level math course using age, race, gender, high school GPA, extent of remedial math need, full-time/part-time status during the first semester of enrollment, unmet financial need, and college GPA as predictors. Of the 625 students who completed the remedial math sequence, 380 (60.8%) enrolled in a college-level math course during the two academic years following initial enrollment.

A test of the full model against a constant only model was statistically significant, indicating that the predictors as a set reliably distinguished between those who completed the remedial math sequence and those who did not (chi square= 19.022, p < .05 with df= 8). Nagelkerke's R-square of .041 indicated an overall weak relationship between prediction and grouping. Prediction success overall was 63.2% (93.2% for enrollment and 16.7% for non-enrollment), which was slightly higher than the null model prediction success rate of 60.8%. Table 19 includes the Model Summary.

Table 19. Model Summary for Model 3

	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
Step 1	818.021[a]	.030	.041

The Wald criterion demonstrated that remedial math need made a significant contribution to prediction (p=.001). None of the other variables (age, full-time enrollment, race, gender, high school GPA, unmet financial need, college GPA) were significant predictors. Table 20 shows the variables included in the model and their relative contribution to prediction.

Table 20. Variables in the Equation for Model 3

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1ª	AGE	.027	.020	1.756	1	.185	1.027
	FULLTIME	.125	.208	.361	1	.548	1.133
	WHITE	.067	.171	.153	1	.695	1.069
	GENDER	-.108	.176	.380	1	.538	.897
	REMEDIAL NEED	-.257	.074	12.072	1	.001	.773
	HS GPA	.115	.091	1.592	1	.207	1.122
	COLLEGE GPA	-.138	.091	2.310	1	.129	.871
	UNMET NEED	-.103	.086	1.437	1	.231	.902
	CONSTANT	.573	.428	1.791	1	.181	1.773

The Exp(B) value for the variable REMEDIAL NEED indicated that with each one unit increase in remedial need, enrollment in a college-level math course was .773 times less likely. For example, a student with a 19 math ACT sub-score is .773 times as likely as a student with a 19 sub-score to enroll in a college-level math course. Likewise, a student with a 15 sub-score is .357 times as likely as a student with a 19 sub-score to enroll in a college-level math course. Therefore, the more remedial need a student has, the less likely they are to enroll in a college level course, even when they have completed the remedial math sequence.

Model 4: The Conditional Probability of Passing a College-Level Math Course

Model 4 explored the conditional probability of completing a college-level math course with a grade of C or better among the 380 students who enrolled in a college-level math course. A multiple logistic regression main effects analysis was conducted to predict obtaining a grade of C or better in a college-level math course using age, race, gender, high school GPA, extent of remedial math need, full-time/part-time status during the first semester of enrollment, unmet financial need, and college GPA as predictors. Of the 380 students who enrolled in a college-level math course, 206 (54.2%) passed the course with a grade of C or better.

A test of the full model against a constant only model was statistically significant, indicating that the predictors as a set reliably distinguished between those who received a grade of C or better and those who did not (chi square= 22.441, p < .05 with df= 8). Nagelkerke's R-square of .077 indicated an overall weak relationship between prediction and grouping. Prediction success overall was 60.5% (75.2% for C or better and 43.1% for less than a C), which was higher than the null model prediction success rate of 54.2%. Table 21 includes the Model Summary.

Table 21. Model Summary for Model 4

	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
Step 1	501.653[a]	.057	.077

The Wald criterion demonstrated that only college GPA made a significant contribution to prediction (p=.001). None of the other variables (age, full-time enrollment, race, gender, remedial math need, high school GPA, and unmet financial need) were significant predictors.

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Table 22 shows the variables included in the model and their relative contribution to prediction. The Exp(B) value for the variable COLLEGE GPA indicated that when college GPA increases by one standard deviation (.90428), the odds ratio is approximately 1.560 greater. For example, a student with a college GPA of 3.07 is 1.560 times more likely to complete a college-level math course with a grade of C or better than a student with a college GPA of 2.17.

Table 22. Variables in the Equation for Model 4

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1ª	AGE	.024	.026	.806	1	.369	1.024
	FULLTIME	.212	.267	.632	1	.427	1.236
	WHITE	-.051	.221	.053	1	.819	.951
	GENDER	-.028	.225	.015	1	.902	.973
	REMEDIAL NEED	-.152	.098	2.415	1	.120	.859
	HS GPA	.029	.114	.067	1	.796	1.030
	COLLEGE GPA	.445	.118	14.294	1	.000	1.560
	UNMET NEED	.150	.114	1.724	1	.189	1.161
	CONSTANT	.073	.546	.018	1	.893	1.076

Synthesis

At the conclusion of data analysis, the researcher reviewed all findings. Most interesting to the researcher was that each model had a different set of significant predictors, that age was

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found to be a significant predictor within the first two models, and that race was not found to be a significant predictor at any juncture within the remedial process. The magnitude of attrition (88.2%) at the first step within the remedial process (enrollment in a remedial course) was also noteworthy and warrants much further investigation. The researcher then began the process of cross-referencing the research base to discern differences and similarities between the major findings of other scholars and the major findings of this study. In addition, the researcher began to formulate the scholarly, practical and policy implications of this study's findings. Lastly, the researcher contemplated the limitations and delimitations of this study and formulated proposals for future research.

CHAPTER 5: DISCUSSION

This study sought to better understand the points at which students fail to progress within the remedial math process, and to statistically model the pre- and post-college entry predictors of that attrition. The study also had a particular focus upon the effect age has on students' ability to successfully remediate. Findings indicate that for each step in the remedial process (enrollment in a remedial math course, completion of the remedial math course sequence, enrollment in a college-level math course, and completion, with a grade of C or better, of a college-level math course), different factors predict attrition. With regards to the effect age has, this study's findings reveal that age matters only during the first two stages of remediation (enrollment in a remedial math course and completion of the remedial math sequence) and that its effect is different for each of the stages, with older students having decreased odds of enrolling in a remedial math course but having increased odds of completing the remedial math sequence. This chapter will delve deeper into these findings by discussing how they are similar and dissimilar to the findings of other studies; explore the scholarly, policy and practical implications of the findings; acknowledge the limitations and delimitations of this study; and propose ideas for future research.

Predicting Remedial Math Attrition: Which Factors Matter and When?

This study confirmed that the remedial process is indeed an attrition process in which students, at each step, fail to progress. This is in keeping with previous research (Bahr, 2010; Bailey et al., 2009; Bahr, 2012; Frye, 2014). Where this study's findings differ however is within the magnitude of attrition at each step. Nationally, 22% of students referred to remediation complete the remedial course to which they are referred and the associated college-level course within two years (Complete College America, 2012). In total, less than 2% of the

students in this study had successfully remediated (passed, with a grade of C or better, a college-level math course) following two years from their initial enrollment in college. Whereas Bahr (2012), in a statewide study in California, found no "large-scale 'exodus' from remedial math at any particular step of the sequence" (p. 676), this study found large attrition rates at several junctures (88% attrition in the first step, 53% attrition in the second step, 40% attrition in the third step, and 45% attrition in the fourth step). It should be noted, however, that Bahr's (2012) study looked only at the progression of students who enrolled in a remedial math course. This study began its analysis of attrition at the point of remedial referral.

The greatest obstacle: enrollment in a remedial math course. The first step in the remedial process (enrolling in a remedial math course) was found to be the greatest attrition point, with 88.2% of students failing to enroll in a remedial math class over the course of two academic years. While other researchers have found similar patterns (Bailey et al, 2009; Grubb & Cox, 2005; Roska et al, 2009), the magnitude of the attrition found in this study was much larger than the attrition rate found in previous studies. For example, utilizing nationwide data, Bailey et al (2009) found that 27% of students referred to remedial math education did not enroll in any remedial course. In a statewide study in Virginia, Roska et al (2009) found that approximately half of students referred to remediation did not enroll in any remedial course over a four year period.

These high attrition rates could be due to confusion among students about the point of remedial coursework, or could signal a strong diversionary impact in which students' collegiate aspirations are deflated. Grubb and Cox (2005) hypothesize that such low enrollment rates may be attributable to students not understanding the value of remedial courses as such courses typically do not count towards a degree. Johnson (2012) on the other hand found a strong

emotional response to remedial referral among students in a community college in Washington, DC. She found students' responses to developmental placement to contain "the greatest concentration of emotional responses than any other aspect of their college experience to date," with students using words such as "sad," "upset," and "disappointed" to describe the experience (p. 80). She goes on to describe the reactions as two fold, with students first reacting emotionally and then more logically, finally accepting the placement as a rationale facet of their college experience. It should be noted that Johnson's (2012) study included only those students who matriculated into remedial coursework. Perhaps students who do not enroll in remedial coursework are those who fail to move beyond the emotional response to placement.

Crisp and Delgado (2014), utilizing a national data set and propensity score matching (PSM), found that students with remedial need who enroll in remedial math coursework and those who do not are significantly different in terms of gender, race, first-generation status, high school GPA, and high school course-taking patterns. It should be noted however that Crisp and Delgado's (2014) study was limited to a specific subset of remedial education students-specifically, students who are between 18-24 years of age who entered a community college with the expectation of transferring to a four-year institution. Nonetheless, this study, like Crisp and Delgado's (2014) study, found gender and high school GPA to be significant predictors of enrollment in a remedial math course. In addition, age, full-time enrollment during the first semester, and college GPA were also found to be significant predictors of enrolling in a remedial math course. The findings on age will be discussed later in this chapter.

Full-time enrollment was found to decrease the odds (by .666) of enrolling in a remedial math course. This was counterintuitive given that students who enroll in more credits have more opportunity to take remedial math coursework. In other words, assuming that first-term

enrollment behaviors are similar in subsequent terms of enrollment, sheer odds seem to dictate that full-time enrollment in the first term would beget a greater likelihood of remedial math enrollment over the course of two academic years. This finding was also counterintuitive given that some contemporary studies on remedial education have found a positive relationship between increased credit load and remedial education progression (Bahr, 2012; Bailey et al, 2009). Bahr (2012), treating course credit load as a continuous, as opposed to dichotomous (part-time/full-time), variable found greater course credit loads to increase the likelihood of progression within the remedial sequence among community college students throughout California. However, it should be noted again (as noted above) that Bahr's (2012) study focused only upon the progression from initial enrollment in remedial coursework and beyond. Bailey et al (2009) found the odds of remedial progression from referral through passing the gatekeeper course to be 1.50-1.68 times as large among full-time students within a national data set.

In this study, females made up the majority (57.2%) of those referred to remedial math. This is consistent with other research, showing that females are disproportionately represented within remedial math coursework (Bailey et al, 2009; Crisp & Delgado, 2014). In addition to being the majority, t-tests revealed that females, on average, had significantly more remedial math need (in terms of the distance between their placement score and the cut score) than their male counterparts. However, despite their greater remedial need, females were found to be .878 times less likely than males to enroll in a remedial math course. This is in contrast to other studies, which have found females to be more likely to progress through the remedial process (Bailey et al, 2009; Bettinger & Long, 2005; Penny et al, 1998). Bailey et al (2009) found the odds of remedial progression from referral through passing the gatekeeper course to be 1.53-1.56

times (depending upon the depth of their remedial need) as large among female students within a national data set.

This study also found high school GPA and college GPA to be significant predictors of whether or not a student would enroll in a remedial math course. However, the odds for each were opposite. An increase in high school GPA was found to reduce the odds of enrolling in a remedial math course, whereas an increase in college GPA was found to increase the odds. The first finding was somewhat counterintuitive. For every one standard deviation (.5142) increase in high school GPA, the odds of remedial math course enrollment decreased .895 times. This was in contrast to other studies, which have consistently found high school GPA to be a significant predictor of successful remediation (Grimes & David, 1999; Hegedorn et al, 1999; Crisp & Delgado, 2014). Perhaps this finding signals a diversionary impact of referral upon students who, for the most part, were told (vis-à-vis their high school GPA) that they were prepared for college. Being referred to remediation has been found to deflate students' academic aspirations and self-efficacy (Clark, 1960; Attewell et al, 2006; Venezia, Bracco, & Nodine, 2010; Scott-Clayton & Rodriguez, 2012), and it is plausible that this impact may be especially acute among students who perceive themselves as college-ready. Hodara & Jaggars (2014) state succinctly, "many students referred to developmental education successfully completed high school, and confusion and frustration at their placement could translate into an erosion of academic aspirations and commitment" (p. 249).

On the other hand, for every one standard deviation (1.198) increase in college GPA, the odds of remedial math course enrollment increased 1.079 times. Perhaps as students gain confidence in their ability to pass college coursework, they are more likely to enroll in remedial math classes. It should be noted that high school GPA and college GPA were found to be

moderately positively correlated, r= .348, p= .000. This finding is similar to a finding by Barfield and Crosta (2012), who, in a statewide study of community college students found high school GPA and college GPA to be positively correlated, r= 0.21, p= .000. With this finding, they concluded, "the relationship between high school GPA and college GPA is so powerful that it would seem important for colleges to more fully consider this measure in deciding on placement" (p. 39).

A 50/50 shot at persevering: completion of the remedial sequence. The second step (completing the remedial math sequence) was found to be the second greatest attrition point, with 53.1% of students failing to complete the remedial math sequence over the course of two academic years. Findings revealed age, extent of remedial math need, unmet financial need, high school GPA, and college GPA to be significant predictors of completing the remedial math sequence. Again, the findings on age will be discussed later in this chapter.

High school GPA was found to be a significant predictor of remedial sequence completion, just as it was found to be a significant predictor of enrollment in a remedial course. However, while high school GPA was found to be a negative predictor of remedial course enrollment, it was found to be a positive predictor of remedial sequence completion. With every one standard deviation (.4773) increase in high school GPA, the odds of completing the remedial sequence increased by 1.182 times. This is promising (given the counterintuitive finding regarding enrollment in a remedial math course) because it says that there is some validity in high school GPA as a predictor of college success after all. While overall high school GPA may not portend college-level math readiness per se (at least in so far as the placement cut score goes), it may signal some level of grit or ability to persevere. This finding is also consistent with prior research showing that high school GPA is a valid predictor of remedial success (Hickson &

Dowdy, 2014; Scott-Clayton, 2012), and to some extent a more powerful predictor than placement exam scores (Willet & Jeff, 2014; Belfield & Crosta, 2012). Utilizing statewide community college data, Barfield and Crosta (2012) found the correlation between high school GPA and outcomes in six levels of math and English remedial courses to range between 0.34 and 0.36. In contrast, the researchers found the correlation between eight different placement exam scores and outcomes in the same six levels of remedial courses to range between 0.08 and 0.18 (Barfield & Crosta, 2012).

This study also found that for every one unit below the ACT placement cut score of 19, the odds of a student completing the remedial sequence were reduced by .583. This finding is consistent with prior researcher (Bailey et al., 2010; Jaggars & Hodara, 2011; Jenkins, Jaggars, Roksa, Zeidenberg, & Cho, 2009) and makes theoretical sense. The more remedial need a student has, the lower within the remedial sequence the student is placed, resulting in more remedial coursework to navigate prior to enrolling in a college-level math course. Hodara and Smith-Jaggars (2014) hypothesize that longer sequences result in multiple exit points, providing more opportunities for attrition along the path to remediation. In addition, research by Bailey et al (2010) shows that failure to complete the remedial sequence is rarely due to failure of remedial coursework. In a national sample, students who were passing their remedial coursework were found to be just as likely to not enroll in the subsequent course in the sequence as those who were failing their remedial coursework (Bailey et al, 2010).

The total amount of unmet financial need (total cost of attendance minus all aid received) a student had during their first year of college was also found to be a significant predictor of whether or not a student would complete the remedial math sequence. For every one standard deviation increase ($9,984) in unmet need, the odds of completing the remedial sequence

increased by 1.144. This is intuitive given that higher unmet need is typically associated with a higher level of family income, relative to other factors such as the students' dependency status or the total number of dependents a student has. Federal Title IV calculations require granting institutions to calculate into an aid package the students' expected family contribution (EFC). The higher the EFC, the lower the aid package, and the higher the unmet need. The term *need* in this sense is somewhat counterintuitive, but represents the amount of money the student had to pay out-of-pocket, with no assistance from loans, grants, and/or scholarships. This finding is consistent with prior research showing a positive correlation between socio-economic status and academic achievement in terms of educational attainment (Aikens & Barbarin, 2008; Langhout et al, 2009; Orr, 2003).

College GPA was also found to be a significant predictor of remedial sequence completion, with the odds of completion rising by 1.870 times with each one standard deviation (.97739) increase. Again, this is consistent with prior research (Frye, 2014), and is understandable given the correlation between high school GPA and college GPA. While college GPA was also found to be a significant predictor of enrolling in a remedial math course (Model 1), the increase in the odds ratio from Model 1 (1.079) to Model 2 (1.870) is noteworthy.

Extent of remedial need continues to haunt students in college-level math. The third step (enrollment in a college-level math course) was found to be the smallest attrition point, with 39.2% of students who completed the remedial sequence failing to enroll in a college-level math class over the course of two academic years. Only one covariate was found to be a significant predictor at this juncture in the remedial process- extent of remedial math need. For every one unit below the ACT placement cut score of 19, the odds of a student enrolling in a college-level math class were reduced by .773. While it is intuitive that the extent of remedial need is a

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predictive factor of remedial sequence completion, it may not be completely apparent why it would continue to be a predictive factor after students complete the remedial sequence. Despite the conundrum, it is consistent with prior research (Hodara & Smith-Jaggars, 2014; Bailey et al, 2010; Bahr, 2012) and could signal a continued detrimental effect of long remedial sequences. As stated above, the more remedial need a student has, the more remedial coursework the student must navigate prior to enrolling in a college-level math course. Just as Bailey et al (2010) and Bahr (2012) found, despite successfully navigating remedial coursework, students simply fail to take the next step. This could plausibly be due to financial constraints (as remedial coursework may have exhausted personal or grant funds) or simply due to personal constraints (a move, the birth of a child, the loss of a job, etc.). Delaying enrollment in college-level coursework through protracted remedial sequences simply increases the odds that life circumstances may stymie progression and subsequent successful remediation (Hodara & Smith-Jaggars, 2014).

Disappearance of background factors: passing the college-level math course. The fourth and final step (passing, with a grade of C or better, a college-level math course) was found to be the third largest attrition point, with 45.8% of students failing to pass a college-level math class over the course of two academic years. At this final juncture in the remedial process, only one covariate was found to be a significant predictor- college GPA. For every one standard deviation (.90428) increase in college GPA, the odds of passing the college-level math course increased by 1.560 times. This finding is rational given that college GPA, insomuch as it is a predictor of academic engagement and ability to pass coursework, is likely a predictor of passing *any course* for *any student* (formerly remedial or not). What is noteworthy about this finding is not necessarily that college GPA is a significant predictor but rather that at this point in the remedial process no pre-college entry predictors were significant. Instead, at this point, it seems

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that the background factors found to be significant in the prior parts of the process (age, full-time enrollment, gender, remedial need, and high school GPA) were no longer a factor. This finding is not consistent with prior research (Bahr, 2010; Frye 2014; Bahr 2012), but may have promising implications for the effectiveness of remedial education (at least for those students who do make it to this final step in the process). Frye (2014), in a statewide study in North Carolina, found several background factors (gender, race, and Pell recipient status) to be significant predictors of passing a college-level math course with a grade of C or better among students who completed remedial math and enrolled in a college-level math course. Bahr (2010, 2012) also found race and the extent of remedial need to be significant predictors of college-level math success among community college students in California. While this study's finding is contradictory to some prior findings, it does hold promise for the efficacy of remedial education. Finding that the extent of remedial need, especially, was no longer a significant predictor could signal that remedial education, for those who successfully complete it, can ameliorate the effects of math deficiency (at least to the extent that the placement test is a valid measure of math proficiency).

Race. Among all of the covariates included in this study, race (white/non-white) was the only variable not found to be a significant predictor of remedial success at any point in the remedial process. This finding was counter to prior research (Frye, 2014; Bahr 2010; Bailey et al, 2009; Bettinger & Long, 2005; Attewell et al, 2006), and perplexing given that independent samples t-tests found significant differences between Whites and Non-Whites in terms of high school GPA, college GPA, and extent of remedial need (all covariates found to significantly predict remedial education success). This finding could be due to the nature of the data. The researcher had to bifurcate the study populations into a White/Non-White dichotomy due to the

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low number of certain race categories. Aggregating across Non-White categories could have masked some of the effects of race seen in previous studies.

The Effect of Age on the Remedial Process

One of the research questions of this study was whether or not age is a significant predictor of remedial education success. The findings from this study indicate that it is, at least at the first two stages of remediation (enrollment in a remedial math course and completion of the remedial sequence), and the effects are opposite. With each one year increase in age, a student is .964 times *less likely* to enroll in a remedial math course. However, among those students that do enroll in a remedial math course, older students are 1.054 times *more likely* to complete the remedial math sequence. The former finding could indicate an acute diversionary effect of referral among older students, much like that seen among female students, and warrants further research. The finding is however counter to a finding by Johnson (2012), who, in a qualitative study found that older students reacted more positively to remedial placement than younger students. Johnson (2012) states that the older students "had been out of the educational system for some time and either wanted or expected to start at a low level" (p. 80). The latter finding however may be consistent with a finding by Calcagono et al (2006) who found that older students in community colleges in Florida were "more likely to need some remediation (but not a lot) because their basic skills were merely 'rusty' rather than grossly deficient" (p. 23). Because much of the remedial education literature has focused upon traditional-age students or has used age as a control rather than predictor variable, there is limited research with which to compare the odds ratios found in this study. However, utilizing a national data set, Bailey et al (2009) found the odds of remedial progression from referral through passing the gatekeeper course to decrease by 0.995-0.988 times (depending on remedial need) with age. While this is counter to

the findings of this study, it should be noted that the study conducted by Bailey et al (2009) did not look independently at each step in the remedial process as this study did, making comparison somewhat problematic. While finding that age does matter within the first two steps of remediation was important, finding that age does not matter thereafter was also noteworthy. Congruent with the findings of Frye (2014), this study did not find age to be a significant predictor of passing a college-level math course.

Scholarly Implications

This study yielded three findings that have scholarly implications with respect to the theoretical framework. First, the study re-conceptualized Bean and Metzner's (1985) Nontraditional Undergraduate Student Attrition Model to specifically study attrition from the remedial process. This use of the Model is novel. To this point, Bean and Metzner's (1985) Model had been used mostly to study attrition from college. In addition, the study expanded the model with the addition of a variable specific to the study of remedial education attrition. The extent of remedial need (the numeric distance between a given students' placement exam score and the cut score used to refer students to remedial coursework) was added to the background and defining variables within the Model, and was found to be a significant predictor of completing the remedial sequence and enrolling in a college-level math course. Third, finding that race was not a significant predictor of attrition at any point in the remedial process, despite its inclusion within Bean and Metzner's (1985) Model, may have implications for that specific variable's use within future remedial attrition studies. However, that particular finding should be tempered somewhat given this study's bifurcation of race into a dichotomous (White/Non-White) variable. While much further research is needed before the Model is validated as a

comprehensive theoretical framework for understanding remedial attrition, this study may represent a first step towards that end.

In addition, this study found age to be a research-worthy variable within the remedial education research base. As stated previously, much of the remedial education literature has focused upon traditional-age students or has used age as a control as opposed to a predictor variable. By determining that age matters, at least during the first two phases of the remedial process, this study asserts future researchers should consider using age as either a continuous or categorical variable when studying remedial education.

Implications for Policy and Practice

Moving beyond the theoretical, this study also produced several findings for which there are policy and practical implications. These findings and their implications can be categorized into three areas: implications for the PK16 pipeline; implications for placement and referral; and implications for the delivery of remedial education.

This study found that the farther away a students' ACT math sub-score was from the statewide cut score of 19, the less likely the student was to successfully remediate. This finding has implications for the PK16 pipeline. Finding that extent of remedial math need is a significant predictor of whether or not a student will successfully remediate is not necessarily a novel finding as other researchers have found a similar relationship (Bailey et al., 2010; Jaggars & Hodara, 2011; Jenkins, Jaggars, Roksa, Zeidenberg, & Cho, 2009). This study however calculated the odds of successful remediation based upon placement test scores. Prior studies calculated the odds based upon the level of remediation the student was referred to. While level of remediation is often a proxy for a placement test score (as each level has a cut score), the levels and their associated cut scores often differ across colleges and a range of scores may be

referred to any given level. This makes it difficult for policy makers and practitioners to act proactively as high school graduates will go to different colleges (each having its own number of levels and associated cut scores). By calculating the odds of successful remediation based upon ACT scores, this study's findings could aid policy makers and practitioners in developing proactive steps to remediate students with ACT scores that portend an unlikely chance of successful remediation while the students is still in high school. Programs like the Tennessee Seamless Alignment and Integrated Learning Support (SAILS) program, in which students address academic deficiencies during their senior year of high school, hold promise for reducing the number of students who begin their collegiate careers with remedial need (Fain, 2013). The SAILS program has been successful, with 92% of students in the program completing their remedial coursework while still enrolled in high school, allowing them to begin college in college-level coursework (Chattanooga State Community College, 2016).

This study found that high school GPA and ACT score are significant predictors of whether or not a student will successfully navigate the remedial math sequence. This finding has implications for placement policies. Nationwide, including in Louisiana, most students are placed into college-level or remedial coursework based solely or in large part upon their scores on a single test (Hughes & Scott-Clayton, 2011). There is growing interest nationwide in developing multiple measure systems for postsecondary course placement (Bahr et al, 2014). Scott-Clayton (2012) found that combining placement test scores and high school GPA for placement purposes greatly increased placement effectiveness. The findings from this study certainly lend themselves to further exploration of a multiple measures placement policy in Louisiana's community colleges. The Research and Planning Group for California's Community Colleges has embarked upon a collaborative statewide effort, called the Multiple Measures

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Assessment Project (MMAP), to pilot and assess various multiple measures models for academic placement. Thus far the group has built a data warehouse and is in the process of working across 23 community colleges to implement various multiple measures placement programs, collect and analyze data (Bahr et al, 2015).

Perhaps the most disheartening finding from this study is the large attrition rate (88.2%) within the first step of the remedial process (enrollment in a remedial math course). It seems that simply getting students to take the first step towards remediation is the greatest challenge facing Louisiana's community colleges. Without taking that first step, students' odds of successful remediation, completing an associate degree and/or transferring to a four-year university are zero. Hodara and Smith-Jaggars (2014) argue that, "while developmental education may build stronger academic skills among those who complete it, any such developmental effect is overshadowed in the larger population by the strong diversion effect" (p. 250). This study found several groups of students for which a diversion effect seems to be present- older students, full-time students, females, and students with higher high school GPA's, all of which are less likely to enroll in a remedial math course following referral. Several researchers have found the testing process itself to problematic, as students are often unaware that they will be tested when they show up for orientation, or if they are forewarned they are not told of the implications of their score (Venezia et al, 2010; Johnson, 2012). These practices can lead to over-placement into remedial coursework as students take the test wholly unprepared or without knowledge of the importance of their performance, and it is likely that over-placement exacerbates the attrition issue. Communicating clearly to students the importance of the test and then providing them with resources to adequately prepare for the test could assist with over-placement issues. After receiving a multi-million dollar First in the World grant from the U.S. Department of Education

in 2015, Bossier Parish Community College (BPCC), located in Louisiana, began experimenting with the use of free, online, self-paced courses which assist students in preparing for placement testing. The courses include short videos by the college's top remedial instructors (which can be replayed over and over to master concepts), handouts which can be printed for those who prefer more tactile learning, and multiple-choice quizzes with immediate feedback (which can also be retaken an unlimited number of times to assist with test anxiety). The program is still being studied for its effectiveness, but early results show high usage rates of the online courses, with more than a million individuals utilizing the courses in one year (Community College Daily, 2015). Another promising practice may be combining remedial coursework with a college success skills course. In other words, students would be able to address their remedial needs within a more holistic framework of learning other college success skills, such as time-management, locating campus resources, and career planning. College success skills courses have been shown to be effective at increasing retention and progression (Offenstein et al, 2010). Perhaps such courses would provide a greater draw for students.

Lastly, finding that students with greater remedial need have a lower likelihood of successful remediation could signal a need to reevaluate remedial education delivery with respect to sequencing. Insomuch as greater remedial need begets more remedial coursework and the opportunity for more exit points from the sequence (Hodara & Smith-Jaggars, 2014), several researchers have advocated for the acceleration of remedial education (Cho, Kopko, Jenkins & Jaggars, 2012; Edgecomb, Jaggars, Baker, & Bailey, 2011). Acceleration models can take many forms, but the main premise is that they all reduce the amount of time students spend in remedial coursework and accelerate entry into college-level coursework (Edgecombe, 2011).There are two main models of acceleration- compressed courses and mainstreaming with supplemental support

(embedded support). Typically, a compressed remedial course meets for somewhere between 6

and 9 weeks as opposed to the 15 or 16 weeks of a semester-long course. The most often cited

reference for compressed remedial courses held during the academic year is Sheldon and

Durdella (2010). The authors of this report studied a large sample of California community

college students enrolled in compressed courses of varying lengths in English, reading, and

mathematics. They found that the students in the compressed courses consistently completed the

course at higher rates than students in regular length developmental courses. In an extensive

review of the research on compressed courses across disciplines, Daniel (2000) found that a

majority of studies reported students in compressed courses learned as much or more, as

measured by grades and examinations, and completed the courses at rates comparable to students

enrolled in semester long courses.

In terms of mainstreaming, one of the most popular models is that used at the Community

College of Baltimore County (Adams, Gearheart, Miller, & Roberts, 2009). In this model,

students placing in to remedial education are assigned to a college level composition course

along with other students whose test scores exempted them from remedial composition. The

remedial students, however, are also concurrently enrolled in a three-hour a week supplemental

class. During the supplement course, the instructors of the college-level course work with

students to develop their study skills and improve their writing. Adams, Gearheart, Miller, &

Roberts (2009) report that students participating in this model are much more likely to complete

the course and pass it than are remedial students being remediated in the traditional format. A

study of the Community College of Baltimore County program by the Community College

Research Center also indicated that participating students have higher completion rates and

suggested that the accelerated learning model was more cost-effective than the traditional format (Edgecombe, 2011).

Limitations and Delimitations

There were several limitations to this study. First, there is potential for natural selection bias within the data. Because certain variables theorized by Bean and Metzner (1985) to be important to understanding attrition were unavailable within the data set (hours of employment, outside encouragement, family responsibilities, opportunity to transfer, utility, satisfaction, goal commitment, stress, intent to leave, study habits/skills, use of academic advising, absenteeism, major and job certainty, and course availability), there is the potential for unobserved differences across groups. This is likely the reason for the rather low Nagelkerke R-Square statistics within several of the models within this study. Second, it is plausible that students who did not complete remediation at any of the colleges within the study instead completed remediation at another college where the researcher did not have access to their outcomes. Third, the offering of the various remedial courses and their associated college-level course during the students' time at the college may have affected students' ability to schedule and complete the courses. Whether or not the courses were offered was not part of the study, therefore findings need to be tempered with the understanding that any failed progression may be just as much student choice as it is institutional offering.

Throughout the development of this study, the researcher made methodological decisions based upon the theoretical framework and the remedial education research base. These decisions imposed several delimitations upon the study. First, the researcher decided to relegate the study population to students who started and were referred to remedial education during a fall semester (fall 2013 or fall 2014) and who were considered first-time college students (enrolled in for-

credit coursework for the first, did not transfer in any postsecondary course credit or hold a postsecondary degree at time of entry, or were not concurrently enrolled in high school). Choosing to build the study population around fall semesters means that students who began in a spring or summer semester were excluded from the study. This decision was made because: fall enrollment is routinely larger than spring or summer enrollment across all ten of the colleges in the study; there is little reason to believe that students that start college in the spring or summer are qualitatively different, on average, than students who start in the fall; and it made longitudinal tracking easier. Relegating the study population to first-time college students meant that students with prior postsecondary experience were excluded. This is common practice within remedial education studies (Bahr, 2013) as it represents a means for ensuring that all students in the study are on equal footing.

Second, two of the independent variables (full- or part-time status and unmet financial need) were collected upon entry, with no consideration for whether or not the variable changed during the two years of the study. It is very plausible that the students in the proposed study changed their enrollment status or that their total unmet financial need changed over the course of two years. However, taking changes in these variables into account, from semester to semester (in the case of enrollment status) or year to year (in the case of unmet need), would have made analysis much more complicated. Instead, the researcher hypothesized that these variables, upon entry, represented the students intentions and financial circumstances at the beginning of their remedial education journey and to the extent that those variables affect outcomes, their disposition at entry may have created a remedial education trajectory.

Future Research

With regards to future research, further validation of Bean and Metzner's (1985) Model as a theoretical framework for the study of remedial education attrition is needed. The current study could be replicated in other states, at other types of institutions, and for English remediation. In addition, inclusion of other variables theorized by Bean and Metzner (1985) to be important to understanding attrition (hours of employment, outside encouragement, family responsibilities, opportunity to transfer, utility, satisfaction, goal commitment, stress, intent to leave, study habits/skills, use of academic advising, absenteeism, major and job certainty, and course availability) should be incorporated.

Also, this study should be replicated with the use of multi-level (HLM) logistic regression. Bean and Metzner's (1985) Model is "designed primarily, but not exclusively, for use at a single institution" (p. 529). This is a limitation of the Model with regards to its use in this study, which was a multi-institutional study encompassing ten community colleges in Louisiana. With regards to multi-institutional studies, Bean and Metzner (1985) advise that care be taken to ensure that institutional factors do not interact with other predictor variables. For this reason, institution-level variables should be added to the study and students should be nested within institutions. Osborne (2015) posits that because individuals within certain environments (such as schools) often share certain characteristics, "observations based on these individuals are not fully independent," and he therefore advocates for nested designs within logistic regression (p. 438). Research has shown that many community college students attend colleges closest to their home (Long, 2004; Bettinger & Long, 2009; Hodara & Jaggars, 2014). In a statewide study in Ohio Bettinger and Long (2009) found that approximately 60% of community college students attended a college within 50 miles of their home. Hodara and Jaggars (2014) found similar

patterns within the City University of New York System. It is therefore probable that students within a single institution may be more homogenous than community college students in general, across multiple institutions in different geographic locations. In a study comparing remedial math completers to non-completers across community colleges in North Carolina, Frye (2014) found that moving from a single-level to a multilevel analysis explained more variance, suggesting "within institutional variance was evident in the student data" (p. 194).

Attrition is a complex phenomenon (Tinto, 1982) and is therefore not easily explained through the study of main effects alone. Including interaction terms assists in capturing the effect that explanatory variables have on other explanatory variables. Bean and Metzner (1985) posit that some variables have interaction effects with other variables in the Model, ultimately affecting attrition, albeit in indirect ways. Further research should move beyond main effects in each of the four models and explore interaction terms amongst the covariates.

The high attrition rate (88.2%) within the first step of the remediation process warrants much further research. At this level, qualitative research is likely needed as it may assist in better understanding students' perceptions of referral and remediation, and more importantly how they arrive at the decision to not enroll in remedial coursework. In a qualitative study, Johnson (2012) found much "complexity and divergence of emotions" (p. 80) among students when asked to reflect upon their feelings during the referral process. She found what she describes as a "two-part response" to the placement process, with part one being an emotional response and part two being a "logic-driven response" (Johnson, 2012, p. 80). Most compelling though was her finding that "the student response to developmental placement included the greatest concentration of emotional responses than any other aspect of their college experience" (Johnson, 2012, p. 80). According to Johnson (2012), students used the following words to

describe their emotions to referral: "sad," "upset," "surprised," disappointed," "confused," and "guilt" (p. 80). It should be noted however that Johnson (2012) only interviewed students who persisted with the remedial process. Similar research should be conducted with students who both persist and those who do not.

In Closing

Remediation plays a vital role in promoting access to postsecondary education. It has been a part of American postsecondary education since the founding of the American academy. Its mission is noble- provide assistance to ameliorate academic deficiencies so that all students have a chance to succeed in college-level coursework. However, data indicate that the majority of students referred to remediation will never complete the remediation process. This study sought to understand why. Without knowing where within the process students are most likely to quit and the factors that best predict that attrition, policy makers and practitioners alike have little chance of effectively intervening. In sum, this study laid a foundation for future research into remedial attrition utilizing Bean and Metzner's (1985) Nontraditional Undergraduate Student Attrition Model. It also confirmed age as a research-worthy variable within the remedial education research space. Research is an iterative process and attrition is a complex phenomenon. The researcher hopes that this study serves as a starting point for future research that will eventually turn the bridge to nowhere into a bridge to anywhere a student wishes to go.

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APPENDIX A

**University Committee for the Protection
of Human Subjects in Research
University of New Orleans**

Campus Correspondence

Principal Investigator: Christopher Broadhurst

Co-Investigator: Emily C. Saleh

Date: July 21, 2016

Protocol Title: The Remedial Education Process: Factors Affecting Attrition among
Adult and Traditional-Age Students in Community Colleges

IRB#: 01Jul16

The IRB has deemed that the research and procedures described in this protocol
application are exempt from federal regulations under 45 CFR 46.101category 4, due to
the fact that the research involves the study of existing data that will be recorded by the
investigator in such a manner that subjects cannot be identified directly or through
identifiers linked to the subjects.

Exempt protocols do not have an expiration date; however, if there are any changes
made to this protocol that may cause it to be no longer exempt from CFR 46, the IRB
requires another standard application from the investigator(s) which should provide the
same information that is in this application with changes that may have changed the
exempt status.

If an adverse, unforeseen event occurs (e.g., physical, social, or emotional harm), you
are required to inform the IRB as soon as possible after the event.

Best wishes on your project.
Sincerely,

Robert D. Laird, Ph.D., Chair
UNO Committee for the Protection of Human Subjects in Research

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June 14, 2016

To Whom It May Concern:

This letter confirms that Emily Saleh, an employee of the LCTCS, has made a formal request to utilize LCTCS student data for the purpose of completing a dissertation study at the University of New Orleans (UNO). Her request has been approved with the following stipulations:

(1) That no personally identifiable student information (name, social security number, birth date, student ID number) be accessed, stored or analyzed on any computer other than a password-protected computer connected to a secure server and housed at the LCTCS Office;

(2) That personally identifiable student information (name, social security number, birth date, student ID number) be removed from any data set before it is accessed, stored, or analyzed on any computer housed outside of the LCTCS Office;

(3) That no LCTCS institutions be named within the study without my written consent; and

(4) That she provides to LCTCS IRB approval from UNO prior to conducting any analysis of the data.

Sincerely,

Paul D. Carlsen, PhD
Chief Content Officer

Model 1 Correlations

		AGE	FT_FRSTTRM	WHITE	GENDER	EXT_MATHN EED	Zscore: HS_GPA	Zscore: COLLEGE_G PA	Zscore: UNMTNEED
AGE	Pearson Correlation	1	-.084**	.018	.008	.142**	-.100**	.095**	.072**
	Sig. (2-tailed)		.000	.054	.395	.000	.000	.000	.000
	N	11203	11203	11203	11203	11203	11203	11203	11203
FT_FRSTTRM	Pearson Correlation	-.084**	1	-.012	.002	-.043**	.110**	.111**	-.076**
	Sig. (2-tailed)	.000		.222	.814	.000	.000	.000	.000
	N	11203	11203	11203	11203	11203	11203	11203	11203
WHITE	Pearson Correlation	.018	-.012	1	-.019*	-.163**	.110**	.147**	.019*
	Sig. (2-tailed)	.054	.222		.050	.000	.000	.000	.043
	N	11203	11203	11203	11203	11203	11203	11203	11203
GENDER	Pearson Correlation	.008	.002	-.019*	1	.047**	.159**	.044**	.035**
	Sig. (2-tailed)	.395	.814	.050		.000	.000	.000	.000
	N	11203	11203	11203	11203	11203	11203	11203	11203
EXT_MATHNEED	Pearson Correlation	.142**	-.043**	-.163**	.047**	1	-.126**	-.076**	.040**
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000	.000
	N	11203	11203	11203	11203	11203	11203	11203	11203
Zscore: HS_GPA	Pearson Correlation	-.100**	.110**	.110**	.159**	-.126**	1	.348**	-.032**
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000	.001
	N	11203	11203	11203	11203	11203	11203	11203	11203
Zscore: COLLEGE_GPA	Pearson Correlation	.095**	.111**	.147**	.044**	-.076**	.348**	1	-.060**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000		.000
	N	11203	11203	11203	11203	11203	11203	11203	11203
Zscore: UNMTNEED	Pearson Correlation	.072**	-.076**	.019*	.035**	.040**	-.032**	-.060**	1
	Sig. (2-tailed)	.000	.000	.043	.000	.000	.001	.000	
	N	11203	11203	11203	11203	11203	11203	11203	11203

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Model 2 Correlations

		AGE	FT_FRSTTRM	WHITE	GENDER	EXT_MATHNEED	Zscore: HS_GPA	Zscore: UNMTNEED	Zscore: COLLEGE_GPA
AGE	Pearson Correlation	1	.017	-.064*	.040	.173**	-.100**	.031	.051
	Sig. (2-tailed)		.541	.020	.140	.000	.000	.259	.065
	N	1330	1330	1330	1330	1330	1330	1330	1330
FT_FRSTTRM	Pearson Correlation	.017	1	.009	.000	-.026	.136**	-.072**	.095**
	Sig. (2-tailed)	.541		.740	.994	.352	.000	.009	.001
	N	1330	1330	1330	1330	1330	1330	1330	1330
WHITE	Pearson Correlation	-.064*	.009	1	-.066*	-.142**	.100**	.029	.123**
	Sig. (2-tailed)	.020	.740		.015	.000	.000	.297	.000
	N	1330	1330	1330	1330	1330	1330	1330	1330
GENDER	Pearson Correlation	.040	.000	-.066*	1	.035	.164**	.067*	.116**
	Sig. (2-tailed)	.140	.994	.015		.201	.000	.015	.000
	N	1330	1330	1330	1330	1330	1330	1330	1330
EXT_MATHNEED	Pearson Correlation	.173**	-.026	-.142**	.035	1	-.126**	.014	-.027
	Sig. (2-tailed)	.000	.352	.000	.201		.000	.612	.326
	N	1330	1330	1330	1330	1330	1330	1330	1330
Zscore: HS_GPA	Pearson Correlation	-.100**	.136**	.100**	.164**	-.126**	1	-.006	.321**
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.841	.000
	N	1330	1330	1330	1330	1330	1330	1330	1330
Zscore: UNMTNEED	Pearson Correlation	.031	-.072**	.029	.067*	.014	-.006	1	-.026
	Sig. (2-tailed)	.259	.009	.297	.015	.612	.841		.348
	N	1330	1330	1330	1330	1330	1330	1330	1330
Zscore: COLLEGE_GPA	Pearson Correlation	.051	.095**	.123**	.116**	-.027	.321**	-.026	1
	Sig. (2-tailed)	.065	.001	.000	.000	.326	.000	.348	
	N	1330	1330	1330	1330	1330	1330	1330	1330

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Model 3 Correlations

		AGE	FT_FRSTTRM	WHITE	GENDER	EXT_MATHNEED	Zscore: HS_GPA	Zscore: UNMTNEED	Zscore: COLLEGE_GPA
AGE	Pearson Correlation	1	.013	-.070	.031	.260**	-.122**	.041	.099*
	Sig. (2-tailed)		.752	.079	.438	.000	.002	.303	.013
	N	625	625	625	625	625	625	625	625
FT_FRSTTRM	Pearson Correlation	.013	1	-.012	-.011	-.043	.203**	-.044	.097*
	Sig. (2-tailed)	.752		.769	.774	.286	.000	.274	.015
	N	625	625	625	625	625	625	625	625
WHITE	Pearson Correlation	-.070	-.012	1	-.065	-.125**	.075	.046	.094*
	Sig. (2-tailed)	.079	.769		.105	.002	.061	.248	.019
	N	625	625	625	625	625	625	625	625
GENDER	Pearson Correlation	.031	-.011	-.065	1	.079*	.146**	.066	.165**
	Sig. (2-tailed)	.438	.774	.105		.047	.000	.101	.000
	N	625	625	625	625	625	625	625	625
EXT_MATHNEED	Pearson Correlation	.260**	-.043	-.125**	.079*	1	-.094*	.071	.073
	Sig. (2-tailed)	.000	.286	.002	.047		.019	.074	.067
	N	625	625	625	625	625	625	625	625
Zscore: HS_GPA	Pearson Correlation	-.122**	.203**	.075	.146**	-.094*	1	-.015	.310**
	Sig. (2-tailed)	.002	.000	.061	.000	.019		.706	.000
	N	625	625	625	625	625	625	625	625
Zscore: UNMTNEED	Pearson Correlation	.041	-.044	.046	.066	.071	-.015	1	.011
	Sig. (2-tailed)	.303	.274	.248	.101	.074	.706		.788
	N	625	625	625	625	625	625	625	625
Zscore: COLLEGE_GPA	Pearson Correlation	.099*	.097*	.094*	.165**	.073	.310**	.011	1
	Sig. (2-tailed)	.013	.015	.019	.000	.067	.000	.788	
	N	625	625	625	625	625	625	625	625

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

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Model 4 Correlations

		AGE	FT_FRSTTRM	WHITE	GENDER	EXT_MATHNEED	Zscore: HS_GPA	Zscore: UNMTNEED	Zscore: COLLEGE_GPA
AGE	Pearson Correlation	1	.005	-.127*	.042	.278**	-.051	.070	.112*
	Sig. (2-tailed)		.915	.013	.409	.000	.322	.175	.029
	N	380	380	380	380	380	380	380	380
FT_FRSTTRM	Pearson Correlation	.005	1	.040	-.053	-.032	.198**	-.101*	.109*
	Sig. (2-tailed)	.915		.436	.304	.540	.000	.050	.034
	N	380	380	380	380	380	380	380	380
WHITE	Pearson Correlation	-.127*	.040	1	-.021	-.175**	.095	.076	.078
	Sig. (2-tailed)	.013	.436		.688	.001	.064	.138	.128
	N	380	380	380	380	380	380	380	380
GENDER	Pearson Correlation	.042	-.053	-.021	1	.065	.155**	.111*	.166**
	Sig. (2-tailed)	.409	.304	.688		.208	.002	.030	.001
	N	380	380	380	380	380	380	380	380
EXT_MATHNEED	Pearson Correlation	.278**	-.032	-.175**	.065	1	-.079	.142**	.087
	Sig. (2-tailed)	.000	.540	.001	.208		.122	.006	.089
	N	380	380	380	380	380	380	380	380
Zscore: HS_GPA	Pearson Correlation	-.051	.198**	.095	.155**	-.079	1	.025	.269**
	Sig. (2-tailed)	.322	.000	.064	.002	.122		.624	.000
	N	380	380	380	380	380	380	380	380
Zscore: UNMTNEED	Pearson Correlation	.070	-.101*	.076	.111*	.142**	.025	1	.016
	Sig. (2-tailed)	.175	.050	.138	.030	.006	.624		.753
	N	380	380	380	380	380	380	380	380
Zscore: COLLEGE_GPA	Pearson Correlation	.112*	.109*	.078	.166**	.087	.269**	.016	1
	Sig. (2-tailed)	.029	.034	.128	.001	.089	.000	.753	
	N	380	380	380	380	380	380	380	380

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

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VITA

Emily B. Campbell was born in Baton Rouge, Louisiana. She obtained her Bachelor's degree in Secondary Education and Teaching from Louisiana State University in 2004, and a Master's degree in Public Administration in 2009.   Emily is currently the Executive Director of Enrollment Management and Student Affairs for the Louisiana Community and Technical College System. Prior to her work with the Louisiana Community and Technical College System she served as a Senior Policy Analyst for the Louisiana Board of Regents and as the Associate Registrar and Institutional Research Analyst for the Louisiana State University Paul M. Hebert Law Center. Before beginning her career in postsecondary administration, she was a high school Social Studies teacher at Baton Rouge Magnet High School. Emily's research is focused upon improving outcomes for students referred to remedial education through evidence-based policy and practice.