

ACADEMIC ABILITIES AND NONCOGNITIVE
TRAITS OF FIRST-TIME FRESHMEN: COLLEGE-
LEVEL & REMEDIAL MATHEMATICS STUDENTS

By

KARL MICHAEL KRUCZEK

Bachelor of Science in Biomedical Engineering
University of Bridgeport
Bridgeport, CT
1987

Master of Mathematics Education
Northeastern State University
Tahlequah, OK
2009

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
Doctor of Philosophy
July, 2017

ACADEMIC ABILITIES AND NONCOGNITIVE
TRAITS OF FIRST-TIME FRESHMEN: COLLEGE-
LEVEL & REMEDIAL MATHEMATICS STUDENTS

Dissertation Approved:

Dr. Juliana Utley

Dissertation Adviser

Dr. Toni Ivey

Dr. Adrienne Redmond-Sanogo

Dr. Susan Stansberry

ACKNOWLEDGEMENTS

I would like to thank Dr. Susan Stansberry, Dr. Adrienne Redmond-Sanogo, and Dr. Toni Ivey, three of my dissertation committee members. I truly appreciate the time, effort, and guidance you have given me during this long and arduous journey. I respected your comments and cherished your encouragement over the past years. A very special thank you goes to Dr. Juliana Utley, my dissertation chair, advisor, and teacher. Your guidance, patience, knowledge, and dedication throughout the entire process, will never be forgotten, and I am extremely grateful to you.

I want to thank Dr. Darryl Linde and Dr. Denna Wheeler as well. Dr. Linde thank you for encouraging me to pursue this degree, and then providing me a teaching schedule that afforded me an opportunity to complete all requirements. Working with me to attain this goal meant a lot. Dr. Wheeler, I appreciate your help throughout the data analysis and results chapters of my dissertation. Your expertise and generosity with your time, during the final push towards completion are sincerely appreciated. Thank you!

Lastly, and most importantly, I want to thank my wife and children. To my wife Jennifer, I am thankful for the love, support, encouragement, and the time you granted me during the 7-year pursuit of this PhD. Thank you for tending to the family matters while I was away from home. Without you, there is no way I would have ever finished it. I love you. To my children Sara, Sylvie, and Karsen you mean the world to me. Sara, your pursuit of becoming a licensed physician helped inspire me to finish my degree. I

am so proud that we will be doctors together. Thank you for your love and support. Sylvie and Karsen thank you for being patient while I was away from home, and thank you for your instant love as soon as I saw you the next morning. Your smiles and hugs helped me more than you will ever know!

Name: Karl Kruczek

Date of Degree: July, 2017

Title of Study: ACADEMIC ABILITIES AND NONCOGNITIVE TRAITS OF FIRST-TIME FRESHMEN: COLLEGE-LEVEL & REMEDIAL MATHEMATICS STUDENTS

Major Field: Education

Abstract: First-time freshmen students enter college with varying levels of precollege academic success in mathematics, assorted demographic backgrounds, grit levels, metacognitive awareness, and mindsets (views on the malleability of intelligence). This study at a Midwestern regional university, first examined demographic, cognitive, and non-cognitive characteristics of 159 participants enrolled in three levels of mathematics courses: full-time remediation, part-time remediation (co-requisite college algebra), and college-level mathematics courses that required no remediation. A subgroup comparison on the variables was then conducted to gain an understanding of the differences between the three groups of mathematics students. Lastly, the study investigated variables that predicted academic achievement (final course grades), and retention.

University records provided placement test scores, high school GPA, and ACT scores, while an online self-report survey yielded demographic, grit, mindset, and metacognitive awareness data. Participant high school GPA and ACT scores mirrored state averages, though nearly 50% were enrolled in a mathematics course requiring remediation, which was higher than the 32.5% statewide figure. Demographic background results revealed that nearly three-fourths of the participants were female, nearly half were White, one-fourth Native American, and about 90% under 20 years of age. Non-cognitively, the participants had more of a growth mindset ($M=4.40$), above average levels of grit ($M=3.40$), and higher than average metacognitive awareness ($M=183.4$).

The study revealed differences among the three groups, including significantly higher percentages of full-time remediation students reported their father never attended college. Students' not needing remediation had significantly higher GPA's and ACT scores than the full-time and part-time mathematics remediation students. Full-time remediation students had significantly lower grit, metacognitive awareness, and final grade averages than the non-remediated students.

Hierarchical regression analysis determined grit and ethnicity predicted final grades for students in any remediation course, while grit and high school GPA predicted grades for the non-remediation students. Logistic regression revealed the odds that mathematics remediation students returning (retention) increased as placement test scores and metacognitive awareness increased. Understanding all three characteristics (demographic, precollege cognitive, and non-cognitive) are important because having a deeper knowledge of the students, may help educators provide interventions and opportunities that enable all mathematics students to succeed.

TABLE OF CONTENTS

Chapter	Page
I. INTRODUCTION.....	1
Background of the Problem	3
Statement of the Problem.....	7
Purpose Statement.....	8
Research Questions.....	9
Significance of the Study	10
Theoretical Framework.....	11
Assumptions, Limitations, and Delimitations.....	13
Definition of Terms.....	14
Organization of Study.....	16
Summary.....	17
II. REVIEW OF LITERATURE.....	18
Brief History of College Remediation	19
General Demographics.....	23
Mindset, Grit, and Metacognition.....	35
Summary.....	57
III. METHODOLOGY	61
Research Questions.....	62
Research Design.....	63
Research Setting.....	63
Population and Sample	66
Instrumentation	68
Data Collection	74

Data Analysis	76
Ethical Considerations	77
Summary	78
IV. RESULTS	79
Characteristics of First-time Freshmen Enrolled in Mathematics Courses	80
Demographic Characteristics	80
Cognitive Characteristics	84
Non-Cognitive Characteristics	86
Differences of the Characteristics of the Groups of First-time Freshmen	92
Demographic Characteristics	92
Cognitive Characteristics	97
Non-Cognitive Characteristics	102
Predictors of Academic Achievement of First-time Freshmen Math Students ...	108
Correlational Analysis: Remediation Final Grades & Demographics	111
Correlational Analysis: Remediation Final Grades & Precollege	112
Correlational Analysis: Remediation Final Grades & Non-Cognition	114
Correlational Analysis: No Remediation Final Grades & Demographics	115
Correlational Analysis: No Remediation Final Grades & Precollege	116
Correlational Analysis: No Remediation Final Grades & Non-Cognition ...	117
Hierarchical Linear Regression for Any Student in Remediation	120
Hierarchical Linear Regression for Students Not in Remediation	123
Retention of First-time Freshmen Mathematics Remediation Students	125
Predictors of Retention	127
Summary of Logistic Analysis	130
V. CONCLUSION	131
Discussion of Key Characteristic of All Participants	133
Key Demographics	134
Key Precollege Cognitive Characteristics	135
Key Non-Cognitive Characteristics	136
Discussion of Key Differences in Characteristics Based on Level of Math	137
Key Demographic Differences	138
Key Precollege Cognitive Differences	140
Key Non-Cognitive Differences	140
Discussion on Predictors of Academic Achievement	141
Key Correlations	142

Key Predictors.....	143
Discussion on Predictors of Retention.....	143
Implications.....	144
Recommendations for Future Research.....	147
Conclusion.....	149
REFERENCES.....	151
APPENDICIES.....	168
Appendix A: Institutional Review Board Approval	
Northeastern State University.....	168
Appendix B: Institutional Review Board Approval	
Oklahoma State University.....	169
Appendix C: Adult Consent Form.....	170
Appendix D: Undergraduate Math Student Demographic Survey.....	173
Appendix E: Implicit Theory Of Intelligence.....	175
Appendix F: Grit Scale.....	177
Appendix G: Metacognitive Awareness Inventory.....	179
VITA.....	181

LIST OF TABLES

Table	Page
3.1 Phases of Data Collection	75
3.2 Planned Analyses for Research Questions.....	77
4.1 Demographic Characteristics as a Percent of the Sample by Remediation Group	81
4.2 Descriptive Statistics: Cognitive Variables by Remediation Group.....	84
4.3 Descriptive Statistics for Pre-CPT by Remediation Group	86
4.4 Descriptive Statistics for Mindset by Remediation Group	88
4.5 Descriptive Statistics for Grit by Remediation Group.....	89
4.6 Descriptive Statistics for Metacognitive Awareness by Remediation Group.....	91
4.7 Ethnicity Percentages by Remediation Group	95
4.8 Father’s Education Percentages by Remediation Group	96
4.9 Mother’s Education Percentages by Remediation Group.....	97
4.10 Tukey HSD: Multiple Comparisons of Differences in Group Mean High School GPA’s.....	99
4.11 Tukey HSD: Multiple Comparisons of Differences in Mean ACT Composite and Mathematics Subscale Score by Remediation Group.....	100
4.12 Tukey HSD: Multiple Comparisons of Differences in Group Mean Pre-CPT Scores between Mathematics Remediation Groups.....	102

Table	Page
4.13 Tukey HSD: Multiple Comparisons of Differences in Mean Grit Scores Between Groups.....	105
4.14 Dunnet T3: Multiple Comparisons of Mean Differences in Metacognition Between Groups.....	107
4.15 Descriptive Statistics for Final Course Grades by Remediation Group	109
4.16 Correlation Analysis: Demographic Variables of Any Remediation Group ..	112
4.17 Correlation Analysis: Precollege, Placement Variables and Any Remediation	113
4.18 Correlation Analysis: Non-Cognitive Variables and Any Remediation.....	114
4.19 Correlation Analysis: Demographic Variables of No Remediation	116
4.20 Correlation Analysis: Precollege, Cognitive and No Remediation	117
4.21 Correlation Analysis: Non-Cognitive Variables and No Remediation.....	118
4.22 Hierarchical Regression of Demographics, Precollege and Non-Cognitive variables on Final Grades for the Remediation Group of Students	121
4.23 Hierarchical Regression of Demographics, Precollege and Non-Cognitive variables on Final Grades for the No Remediation Group of Students	124
4.24 Retention Percentages by Group.....	126
4.25 Logistic Regression: Demographics Predicting Retention	128
4.26 Logistic Regression: Cognitive Variables Predicting Retention	129
4.27 Logistic Regression: Non-Cognitive Variable Predicting Retention.....	130

LIST OF FIGURES

Figure	Page
1 Model of the Triadic Reciprocity in Bandura's Social Cognitive Theory.....	11
2 Metacognition and its Subcomponents	50
3 Means Plot of Mindset Scores by Group	104

CHAPTER I

INTRODUCTION

Colleges and universities around the nation open their doors yearly to a diverse and ever-growing population of students. College in the United States of America is no longer only for the rich or academically superior high school graduates. Students from a full range of socioeconomic backgrounds, diverse cultures, and varied levels of academic preparedness are attending post-secondary institutions in order to pursue their career dreams or figure out where their interests may eventually lie. The National Center for Educational Statistics (NCES, 2012) reported a growth from nearly 14 million in 1990 to over 21 million college students in 2011. Furthermore, NCES (2012) projects college enrollment numbers upwards of 23 million by 2023.

With increases in the nation's overall college population, there unfortunately remains a large population of students leaving secondary schools who are not academically prepared for college-level coursework. "Academic preparedness is one piece of the college-readiness puzzle, but, college-ready is more than college-eligible" (Barnes, et al., 2010, p.19). Completing high school makes one eligible, but not necessarily academically ready for college (Conley, 2007). The National Center for Public Policy and Higher Education (2010) reported that the gap between being eligible for college and being ready for college remains too large and unchanged.

As a result of being academically underprepared, a growing number of undergraduate students start their post-secondary academic journey by taking remedial classes. The purpose of a remedial course, or synonymously referred to as a developmental course, is to get the student up to college-level readiness. Mitchell (November 17, 2014) reported that 2.7 million students were enrolled in remedial coursework at colleges and universities nationwide. The NCES (2010) reported that annually, approximately 1.7 million first-time freshmen students take at least one remedial course. While some students require reading and writing remediation, more students require mathematics remediation. Complete College America (CCA) reported that more than one million students begin college each year having to enroll in a remedial course, with over 424,000 of those enrolling in a remedial mathematics course (www.completecollegeamerica.org/SpanningTheDivide, 2013). Unfortunately, less than 50% of the students are successful in their developmental mathematics course on their first attempt (Bahr, 2011). The CCA report stated that nationwide, only 22% of students in a mathematics remediation class “ever enroll in, let alone complete their gateway courses in math” (2013, p.2) within two years, and only 17% of mathematics remediation students across the country will go on to graduate.

While the aforementioned percentages for success in remediation classes appear to be low, for some remediation can be an effective avenue to graduation. A student who successfully completes remedial coursework in the first semester or two are twice as likely to finish their degree, than those who opted not to be remediated (Bahr, 2008). Bahr (2008) added: “Students who remediate successfully in math exhibit attainment that is comparable to that of students who achieve college math skills without the need of

remediation, and this finding generally holds true even across the various levels of initial math skill deficiency” (p. 442).

So why do some of today’s college students who require mathematics remediation succeed while others lose their way and drop out? Instructors may have their own thoughts on this issue, but can they truly answer that question for every student enrolled in a mathematics remediation course? What do educators really know about the mathematics remediation students sitting in their classrooms? Post-secondary institutions may be able to help a greater number of students requiring mathematics remediation be successful if the educators understood more about who these learners are (demographics), what these learners know (cognition), and their beliefs about learning (non-cognitive).

Background of the Problem

Post-secondary remediation did not begin with the current millennial-aged student body. Colleges in 1870’s were very selective in whom they accepted, for only one percent of the population went to college back then. Historically only the academically superior or wealthy students went to college, and the students were required to know Greek, Latin, and a minimal amount of mathematics, or they were most often times not accepted. Of those accepted, some of the early college students still required remediation (Snyder, 1993). Surprisingly, college remediation began even earlier, back in the 17th century at Harvard College when struggling students received help from Greek and Latin tutors (Aycaster, 2001).

While the U.S. had 563 colleges, with a campus-wide enrollment average of only 112 students in 1870 (Snyder, 1993), the post-secondary education enrollments have swelled to more than 20 million students in 2014, enrolled at over 4,700 degree-granting

institutions. In 2014, 68% of graduating high school students entered college, with 69.2% in 2015 (Bureau of Labor Statistics, 2017), which helps to clarify the escalation of freshmen enrollment numbers in recent years. The number of first-time freshmen students requiring remediation in college has increased as well. A significant number of the graduating high school students did not test at college-level readiness on national standardized assessments, which indicates a need for remediation. In 2010 there were approximately 1.7 million first-time freshmen enrolled in remedial classes at post-secondary institutions (NCES, 2011). In the 2010-2011 academic year 16.2% of first-time freshmen enrolled in a mathematics remediation class, while 10%, 7.5% and 7.5% enrolled in English, Reading, and Writing respectively (Kena, et al., 2016). Higher education concerns emerged since more than one-fourth of first-time freshmen enrolled in remedial classes, and too many of those students failed, while public colleges across the nation incurred a one-billion dollar per year remedial education cost for public colleges (Schmidt, 2008). “This is a critical time in terms of remediation policy” (Long, 2014, p. 3).

Studying the large numbers of students nationwide, focusing on their success rates in remediated math and college-level mathematics, along with their retention and graduation rates, may only tell a statistical story of success and failure rates. Addressing this issue requires looking deeper. Like Duckworth (2007) who tried to understand why her 7th grade mathematics students with equal intelligences varied in academic achievement, it is equally important to understand why remediation works for some students while not for others. Remediation appears “to help or hinder students differently by state, institution, background, and level of academic preparedness” (Bettinger,

Boatman, & Long, 2013, p. 99). Additionally, Bettinger et al. (2013) suggested that understanding each student and their differences may help create a more effective remediated course (Bettinger et al., 2013). The type of support each student in a mathematics remediation course needs may vary. A one-size fits all setting or instructional mode does not meet the needs of each individual student. A report by Complete College America (2015) suggested a comprehensive intake process “can help to identify a student’s most pressing academic and nonacademic needs” (p. 4). During this intake process, one might ask what do college personnel need to know about these students to help them achieve success.

Higbee and Thomas (1999) stated “that for educators to be effective, they must have an understanding of how students cognitively process information” (p. 26). Knowing the high school mathematics background of students needing remediation, can be useful and important information. Kuh, Kinzie, Schuh, and Whitt (2005) posited that prior academic ability, easily collected by a college admission office, may be used as a barometer for success. They found prior academic achievement is a key predictor for student success in college. Kamphus (2001) reported Binet’s IQ test has been a proven predictor of academic achievement for more than 100 years. Is success in school based solely on intelligence, i.e., “success comes to only those who score highest on tests from preschool admissions to SAT’s”? (Tough, 2012). How can a student enrolled in a mathematics remediation course succeed in college if they are not academically superior, do not score high on an IQ or admission test or the SAT/ACT?

Fortunately, prior academic achievement is not the only predictor for success today or in years past. Duckworth (2013) stated that non-cognitive traits are as important

to success as cognitively abilities. Tough (2012) took it further, for he claimed that intelligence is not the main predictor for academic success, but rather the character of the individual that matters most. Parents typically contribute to the character building of their children. Demographic information such as parents' educational background coupled with the parents or friends influence on their decision to attend college, are non-cognitive attributes that may play a role in students completing their education (Temple, 2009). There are other attributes that can influence academic achievement as well. Skills such as perseverance, conscientiousness, and self-control are non-cognitive traits central to achieving success (Tough, 2012). Additional non-cognitive characteristics like mindset and grit have also shown to be important factors in academic achievement. While Dweck (2008) stated that having a growth mindset can improve intelligence, Duckworth (2009) declared students who exhibited grit, can persevere through obstacles towards long-term goals. In concordance, Young and Fry (2008) found that undergraduate and graduate education students that know how they learn, monitor their learning processes, and use appropriate strategies to improve learning, exhibit high metacognition, which positively correlated with course grades. Additionally, the beliefs students have about their own academic capabilities, dubbed self-efficacy (Bandura, 1993), play an important role in their motivation to learn (Zimmerman, 2000) and self-efficacy has also shown to be more predictive of academic achievement than a student's measured ability (Farmington, 2013). Crede & Kuncel (2008) concluded in their research that study skills and study habits have "strong and robust relationships with academic performance in college" (p. 439). While Stephens (2005) found correlations between a small set of variables relating previous academic performance and course success in a

study on elementary algebra students, the “only one of six variables chosen for correlation which showed a definite relationship was the overall grade point average from high school” (p. 70). Long (2003) tried to determine relationships between academic achievement and a finite number of academic independent variables. She found no relationship between placement test scores and successful completion of the remediation course. She suggested a need to include more variables “such as number of hours worked, number of credit hours carried in the semester, income, marital status, and other personal variables...” (p. 109).

Many of these studies showed promising results for the variety of students academically underprepared who enroll in remedial courses in colleges and universities nationwide. However, educational leaders need to know more about this population of students, including more demographic information, along with more cognitive and non-cognitive traits these learners bring to their institutions, because too many of our college students cannot successfully navigate the transition from high school to college on their own (Tinto, 2013).

Statement of the Problem

It is apparent from staggering statistics (Bailey et al., 2010; Kemp, 2014; Long, 2014) that too many incoming college freshmen are required to enroll in a remedial mathematics course, and many times these students are not successful. Since too many remedial education programs are experiencing limited successes for some students, institutions are reevaluating their programs and even debating their value. First and foremost, institutions must know that there is not one single set of strategies that will “serve our country’s enormous diversity of students and postsecondary institutions”

(CCA, 2015). Thus, with the continued influx of underprepared students at colleges and universities, educators should gain a deeper understanding of these learners who require remediation.

While previous studies reported predictors for success, not all of these studies focused on students needing mathematics remediation, and they did not include all of the demographic, cognitive, and non-cognitive data collection and analysis in one research study. Nor were there attempts to correlate non-cognitive, cognitive, and demographic information for this population of students. Collecting all of this data during one interval of time during a semester, may help educators and the students themselves, become aware of factors that could be critical toward their success in college and beyond. The first aim of this research study was to determine who these students are in these classrooms. How do college personnel gather and use this information to help individual mathematics remediation students (or entire classrooms) receive the appropriate academic support needed to help them be successful, so these students can achieve their lifetime goals? If the goal of a college or university is to successfully remediate 100% of all developmental mathematics students, then educators have to know more about the students. A good reason to explore the cognitive, non-cognitive, and demographic characteristics of mathematics remediation students may be to help further the knowledge about the predictors for their academic achievement.

Purpose Statement

With millions of student's still requiring remediation at universities nationwide, and with too many of them not succeeding in the past, educational leaders must come to

understand the demographics, academic abilities, and non-cognitive traits these students bring to their post-secondary schools, before academic support strategies and interventions are created in order to help serve this group of students. The purpose of this survey-design quantitative study was to first understand who the students are that come to post-secondary institutions, both academically prepared and underprepared for college-level mathematics coursework. The researcher investigated the demographic characteristics, mindset, level of grit, metacognitive knowledge, and academic performances of both college-level, and remediated mathematics students at a Midwestern regional university. After determining differences in these variables between these two types of students, the next purpose was to determine which variables were predictors of academic success. Lastly, an examination of the retention rates for the remediation students ensued. Thus the research questions guiding this study were:

1. What are the characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of college freshmen enrolled in their first college mathematics course at a Midwest regional university?
2. Are there significant differences in demographic, cognitive, and non-cognitive traits (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) between groups (Full remediation, part remediation and no remediation) of college freshmen based on mathematics course enrollment?
3. Which characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of college

freshmen enrolled in their first college mathematics courses at a Midwest regional university are predictors of academic achievement as measured by final letter grades?

4. Which characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of freshmen students enrolled in a mathematics course requiring remediation at a Midwest regional university, are predictors of retention?

Significance of the Study

Universities in Oklahoma, and across the United States, are being charged with developing co-requisite mathematics courses for the academically underprepared students enrolling in classrooms on their campuses. Currently in Oklahoma, the co-requisite model consists of a traditional 3-hour per week college level course, along with a mandatory two hour per week time frame for extra help. The activities during the two-hour time slot may differ for individual students during this remediation period. This study may help determine a variety of needs these mathematics remediation students require during this supplemental time period. The intended outcome of this research was to generate knowledge that can be shared with college faculty, curriculum developers, and administrators across the state and nation, in order to develop successful remediation programs and support, or interventions, that may help better prepare incoming and currently enrolled college students nationwide.

Theoretical Framework

According to Bandura's Social Cognitive Theory (1989), the thoughts, actions, and behaviors humans partake in are determined by the intertwined environmental and personal factors along with behavior, and operate in a triadic reciprocal relationship (see Figure 1) whereby each influences each other bi-directionally. In other words, triadic reciprocal causation, within social cognitive theory (SCT), implies that thought and behavior are determined by three individual but interweaving factors: (1) personal characteristics, (2) environmental factors, and (3) behavior.

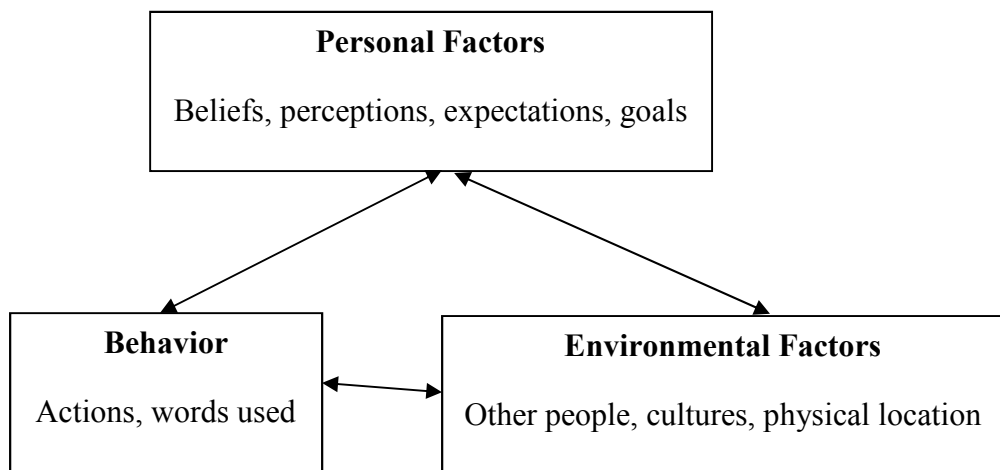


Figure 1. Model of the triadic reciprocity in Bandura's Social Cognitive Theory.

The perpetual interaction between these factors contribute to the continuing development of humans. Bandura (1989) broke down the individual subsystem interactions, starting with the Personal Factors and Behavior (P ↔ B) reciprocity portion of SCT. Here, what “people think, believe, and feel, affects how they behave” (p. 3). For instance, the behavior (actions taken by, words uttered, or plans made) by an individual is

influenced by personal factors like self-efficacy, personality and motivation to learn. In turn, a person's actions and behaviors help determine their thoughts, cognitions, and goals for the future. For the Environmental and Personal Factors (E ↔ P) segment of SCT, environmental factors, including both social and physical surroundings, can influence and change a person's way of thinking or learning. Reciprocally, the beliefs and goals or image of oneself, for example, may affect, strengthen, or otherwise alter, the environment, (i.e., the people they associate with or the physical locations visited). Thirdly, Bandura (1989) discussed the Behavior and Environment (B ↔ E) subsystem, and noted that because "of the bi-directionality of influence between behavior and environmental circumstances, people are both products and producers of their environment" (p. 4). This implies that environmental conditions like an academic setting for example, can influence the behavior and actions taken by the individual in those surroundings. Conversely, the behaviors and actions exhibited by an individual, may impact the people or cultures around them, or the physical environment like a classroom setting.

In summary, the social cognitive theory model demonstrates how personal factors influence the environments we choose, which in turn influence one's behavior in those settings. The reciprocal of that statement is true as well. If we are cemented in a constant and complex triadic reciprocal causative situation, between personality, environmental situations, and behaviors, it appears people can change each of the three. Social Cognitive Theory can help explain how people acquire and maintain certain behavioral patterns, while also providing the basis for intervention strategies (Bandura, 1997).

Bandura's theory was the framework for this study, since students come to universities with varied personalities (Self-efficacies, perceptions and goals), environments (families, cities and cultures), and past behaviors. Understanding the personal, environmental, and behavioral backgrounds of each individual student may help design interventions that will help change or better serve the first-time freshmen entering post-secondary schools across the United States.

Assumptions, Limitations, and Delimitations

The first assumption for this research project was that there will be a continued/future need for freshmen enrolling in college, who are underprepared for coursework, thus requiring mathematics remediation. Secondly, the researcher assumed that the participants in this study were indicative or representative of other students enrolled in mathematics remediation at colleges and universities across this nation. Lastly, it was assumed that all participants understood each question on the survey instruments, and they answered each question honestly.

During the consent process, students were informed that their participation in the study was voluntary, and that their identities and responses were kept anonymous and confidential. This study was limited to first-time freshmen mathematics students who agreed to consent to this research project. The participants were limited to students enrolled at one 4-year Midwestern University, thus results might not be generalizable to all post-secondary institutions.

This study focused on variables related to student demographics, cognitive and non-cognitive traits. The demographic variables included gender, age, ethnicity, marital status, number of children, parent's educational background, grade in last mathematics

class, persons of influence, career plans, and study habits. The cognitive variables considered were overall high school GPA, mathematics high school GPA, overall ACT score, and student mathematics sub-score on the ACT. Non-cognitive variables examined included students mindset (growth or fixed), their level of grit and the awareness of their own metacognition.

Definition of Terms

- *Academic achievement* – there are a variety of outcome measures educators use to determine academic achievement. For this study, academic achievement was determined by participant final letter grades in their course and their post-placement scores.
- *Cognitive ability* – “is the capacity to perform higher mental processes of reasoning, remembering, understanding, and problem solving” (Bernstein, et al., 2008). For this study, the participant precollege academic measures were used to denote their cognitive abilities.
- *Grit* – a person’s capacity to sustain both effort and interest, through challenges and adversity, over extended time towards achieving a goal (Duckworth, 2007).
- *Mathematics Remediation* – for this study participants were in a full-time remediation course, a partial (part-time) remediation course or in a course not requiring remediation.

Full Remediation: Elementary Algebra is a review of basic algebra concepts including signed numbers, fractions, percent’s, exponents, order of operations, factoring, algebraic fractions, linear equations, inequalities,

and basic word problems.

Intermediate Algebra is traditionally the second course in the full remediation sequence. Topics include radicals, rational expressions, factoring, linear equations and inequalities, absolute value, complex numbers, and quadratic equations

Partial Remediation is the Co-Requisite College Algebra class. Two hours per week of remediation and 3 hours per week of traditional College Algebra material

No Remediation: College-level courses including College Algebra, Applied Math, Trigonometry, Statistics, Discrete Math, Calculus, and Intro to Proof.

- *Mindset* – refers to ones’ belief in the malleability of intelligence (Dweck, 2007). According to Dweck, an individual with a fixed mindset views intelligence as being fixed (the brain is impermeable) while an individual with a growth mindset views intelligence can grow (the brain is malleable).
- *Metacognition* – According to Martinez (2006), metacognition is “the monitoring and control of thought.” The two components that comprise metacognition according to Schraw (1994, 1998) are knowledge of cognition and regulation of cognition.
- *Non-cognitive traits and skills* – skills encompass those traits that are not directly represented by cognitive skills or by formal conceptual understanding, but instead by socio-emotional or behavioral characteristics that are not fixed traits of the personality, and that are linked to the educational process, either by being

nurtured in the school years or by contributing to the development of cognitive skills in those years (or both)” (Garcia, 2014, p. 6)

- *Placement test* – The institution for this study, uses the CPT ACCUPLACER placement test. Students entering the university with an ACT below 19 are required to take the placement test. The CPT places a student in a course, based on their score. Scores below 44 place students in Elementary Algebra. Scores between 44 and 74 place students in Intermediate Algebra, while scores 75 or above allow students to enroll in college-level mathematics. A post-placement test at the end of the semester, for the students enrolled in a remedial mathematics course, helps determine whether students have become more proficient in mathematics (i.e., remediation has successfully occurred).
- *Retention* – refers to enrolling back in school the ensuing semester.

Organization of the Study

This study is organized in a five-chapter format. Chapter I provides a basic introduction into the study, the focus of the study including the problem, purpose and significance of the study, as well as the research questions and key terms. Chapter II includes a review of the literature related to remedial mathematics including history, successes, and prior research. Also included is a review of the literature regarding mindset, grit, metacognition, and the demographic makeup of students requiring mathematics remediation. In Chapter III, the research design and methodology of this study is outlined such that, potential replication of this study could be conducted by others in the future. This section specifically addresses the goals and objectives of the study, the overall research approach, the variables examined, the instruments used to

collect the data, and the research design. Chapter IV presents the analysis of the data, while Chapter V presents the findings of the study, the conclusion, implications, and calls for additional research.

Summary

There has continued to be a need to offer remedial mathematics at many colleges in America (Fine et al., 2009). Knowing the cognitive backgrounds, ACT scores and GPA's, of students enrolled in mathematics remediation course may be helpful. However maybe understanding how students think, whether they persevere or whether they have career goals, are equally important. The purpose of this study was to gain a deeper understanding of who these mathematics remediation students are, and whether their cognitive, non-cognitive, and demographic information predict successful remediation, while comparing this cohort of students to freshmen students enrolled in college-credit mathematics courses. Determining factors that may contribute to, thus predict student success, may help add to the research on remedial mathematics at the post-secondary level. Reported in the ensuing chapters are a review of the relevant literature, a description of research methodologies, analyses of the data, discussions, and implications for future research.

CHAPTER II

REVIEW OF THE LITERATURE

The first purpose of this study was to gain a deeper understanding of the first-time freshmen college students enrolled in the various levels of mathematics course, including remediation and college-level mathematics courses, at a Midwestern university. Second, this study aimed to determine which characteristics impact the academic success of all mathematics students, and determine how mathematics remediation students differ from college-level mathematics students. The third goal of the study was to determine which characteristics of students requiring remediation, predict their retention.

This chapter begins with a focus on research related to mathematics remediation at post-secondary institutions, including customary demographics of the students requiring mathematics remediation, and the past, present and future need for such courses in institutions of higher education. The chapter then delves into research regarding other characteristics of students in remediated mathematics classes, including mindset, levels of grit, and metacognition. A discussion of the research regarding successes and failures, and retention rates of school mathematics remediation programs follows. The chapter concludes with an analysis of how and what characteristics may be predictors of the academic success and retention of college students enrolled in remediated mathematics courses.

Synthesizing the above research affords the researcher of this study the opportunity to first determine the gaps in college remedial mathematics research by initially determining and finding and understanding differences between students in mathematics remediation and those not required to enroll in such a course. This review of literature aimed to determine any gaps in this important area of concern, for the overall intent of this study was to uncover potential implications for improving college remedial mathematics programs for the betterment of students enrolled in these courses.

Brief History of College Remediation

Remediation at the college level is not new. The millennial students of today enroll in remedial mathematics classes in order to develop and hone their mathematics skills at college and university campuses across the United States, just as underprepared mathematics students had to do at City University of New York (CUNY) during the open enrollment era of the 1970's (Renfro & Armour-Garb, 1999). In their report to then Mayor Rudy Giuliani, Renfro and Armour-Garb (1999) summarized the history of remediation at CUNY, as well as the history of United States post-secondary remediation, beginning with Harvard College during the mid-seventeenth century. How and why did the numbers of students requiring college remediation grow from the limited number of Harvard students needing a Greek or Latin "refresher" in the 1640's, to the nearly 3-million students today needing extra math, reading and/or writing skill development? (Snyder, 1993; Mitchell, 2014).

To begin, one must understand that it was not mandatory to attend primary and secondary schools in the United States during the mid-1600's. As a result, only one-

percent of the academically elite, socially connected or wealthy students attended the exceedingly selective colleges back then (Renfro & Armour-Garb, 1999; Snyder, 1993). From the establishment of these institutions through to the 1860's, students attending prestigious colleges such as Harvard, Yale and Princeton were mainly privileged white males. As the United States expanded toward the west, journeyed through world wars, welcomed an inpouring of immigrants, encountered economic turns and federal legislative changes, a need for more colleges in America arose to meet the desires of the ever-changing and increased population of students who sought post-secondary education (Arendale, 2002). For some, the intent to attend college remained similar to the early seventeenth century student, while for others the goal was to gain agricultural, engineering, and other vocational knowledge for a career in these fields.

All institutions of higher education that were established during the ensuing years of the American growth in post-secondary schooling, were not of equal prestige or selectiveness. Ivy-league schools of the east and similar demanding schools established in the west were, and still are, deemed highly selective, while state and regional universities along with community colleges were not as prestigious and may be considered non-selective, yet they still offered pertinent degrees. During the time when America experienced increases in the number of post-secondary schools and types of degree-granting institutions, came increases in varied levels of academic readiness, resulting in a response and expansion in remediation or developmental education courses and programs. In the early twentieth century nearly half of the students applying to the selective and prominent colleges did not meet the expected entrance exams scores, thus required remediation (Arendale, 2002). Today, non-selective "public institutions provide

the bulk of remediation, and serve as the point of entry for 80 percent of four-year students and virtually all two-year students” (Bettinger & Long, 2008, p. 737). The intent of remediation in 1850, the ensuing decades, and today in 2016, remains the same; that is to create an opportunity for students to gain necessary knowledge and skills, lacking from their high school education, to be successful in college and the job world (Long & Boatman, 2013). As in earlier decades, in addition to today’s high school graduates there are also adult students returning to college because of job losses or career changing aspirations, as well as recent immigrants, who must also enroll in developmental or remedial courses in order to remove deficiencies or re-sharpen past mathematics skills. There is therefore a continued and a great need for remediation.

How have the numbers and percentages of enrollment in remedial mathematics courses changed over the last 50 years? In the 1960s alone, the undergraduate enrollment numbers doubled to 4 million, with a total post-secondary enrollment of 8.6 million (Centra, 1978). College enrollment increases did not stop, as 1980 college enrollment numbers soared to nearly 12 million. With these increases, came an increase in students requiring mathematics remediation. Narode (1989) reported a 165% increase in students enrolling in remedial math, general math, or algebra at universities during the two decades between 1960 to 1980. He added that “two-year colleges report that 42% of mathematics enrollments in 1980-81 were in remedial courses” (Narode, 1989, p. 3). When examining the years between 1980 and 2013, the United States realized an increase in the number of 2-year and 4-year degree-granting schools accepting students. There were an eye-opening 230 more 2-year and more than 1,000 more 4-year degree-granting institutions in 2013, than there were in 1980. This translates as increases in college

enrollment numbers from the aforementioned roughly 12 million in 1980 to just under 14 million in 1990 to over 20 million public, private 2-year and 4-year undergraduate and Post-baccalaureate in 2013 (NCES, 2014). The need for mathematics remediation also grew during these decades as enrollment in and number of new higher education institutions expanded.

For instance, in the 1983-1984 academic year approximately 25% of all college freshmen took a remedial mathematics course (Schonberger, 1985). With 2.444 million first time freshmen attending 2- and 4-year higher education institutions that calendar year, this equates to about 611,000 remedial mathematics students (NCES, 2000). In 1995, of the estimated 2,128,000 freshmen enrolled in a remedial course at a public or private 2-year or 4-year institution, 24% were taking a remedial mathematics course (NCES, 2000). According to this study, this total of over 510,000 students represented a significant increase from the totals from 1989 (NCES, 2000), yet lower than 1983-1984 numbers. In a twenty-first century study, Brothren and Woombach (2004) discussed the continued need, when they indicated that 78% of all higher education institutions and nearly 100% of all community colleges continue to offer remedial coursework. The need endured through the ensuing decade as indicated in the NCES (2010) report of over one million first-time freshmen students each year enrolling in at least one remedial course, which was roughly one-third of the entering freshmen. A Complete College America (Vandal, 2013) study stated that more than 42% of these million first-time freshmen require mathematics remediation. In Oklahoma, the setting for this study, the percentages were around 39%. The Oklahoma State Regents for Higher Education (OSHRE) state that there were 34,325 first-time freshmen enrolled in college remedial

courses during the Fall 2012 semester (OSHRE, 2103). While some students require reading and writing remediation, more students require developmental mathematics. In Oklahoma only 34% of high school students taking the ACT in 2015, did meet the mathematics benchmark, indicating college readiness, implying 66% were underprepared for college-level mathematics.

One may notice a slight rollercoaster effect on the numbers of enrollments in remedial mathematics courses at the college level during the 80's and 90's, through the early twenty-first century to today's student body. However, these modest upward and downward variations still paint a picture for a current need for post-secondary institutions to accommodate this population of students requiring mathematics remediation. The majority of these colleges and universities must continue to address a percentage of the over 23.5 million students that were enrolled in Title IV post-secondary institutions in the United States in 2014-2015 and maybe even higher estimates for the future. A discussion on who these students will be in the future, might first entail understanding who the students were in the past.

General Demographics

Students enter college with differing demographic, family, educational backgrounds. A discussion on relevant research pertaining to these type of student characteristics follows.

Gender. As indicated earlier, the majority of college students in 1645-1850 were white males. By the year 1870, 21% of the college enrollment was comprised of women, while at the turn of the twentieth century this percent grew to nearly 40%, and as of 1979 there was a higher percentage of women enrolled in college in comparison to men

(Snyder, 1993). In 2004 more female high school students versus male, aspired to go to college, sought personal guidance, searched for college information, took a standardized test, and applied to postsecondary schools (NCES, 2013). The trend continued, as 2014 data indicates 56% of the undergraduate enrollment were women (NCES, 2016). As a result of a higher population of women versus men attending college, comes an inclination of a higher enrollment percentage in remedial mathematics classes. A study by NCES (2013) may agree with this conjecture, since the report indicated in 2011, 49% of male students met the ACT mathematics benchmark for college readiness compared to only 41% of females meeting the same minimum benchmark for mathematics readiness. The same report also indicated that every year between 2008 and 2011, male students had higher SAT mathematics sub-scores than their female counterparts (NCES, 2013), which may suggest a lower need for remediation. Lesik (2006) claimed while females consistently score lower on standardized tests of mathematics, compared to males, there were no differences in the classroom. He added though, a larger proportion of female and minority students fail remedial mathematics courses compared to male and white students. Correspondingly, in 2007-2008, 36% of all first-time freshmen reported taking a college remedial course, while a lower percentage of these were male (33%) versus 39% being female. Adding to the confusion regarding the sexes though, NCES (2012) found more male students withdrew from the course, and more dropped out of college as well.

Ethnicity. As for the variety of ethnicities of students enrolled at degree-granting post-secondary institutions, the percentages have changed. In the recent NCES (2016) report on enrollment data, the number of white undergraduate students between 1980 and

2014 varied beginning with just less than 8.5 million in 1980, soaring to nearly 11 million in 2010, and falling back to approximately 9.6 million students in 2014. More dramatic were the changes in Hispanic and African American undergraduate enrollment numbers between those decades. The biggest increase in population during this time frame was that of the Hispanic students, where the population of undergraduate students went from 433,000 in 1980, to more than 1.3 million in 2000, soaring to nearly 3 million in 2014. The African American undergraduate student population also rose during those years from more than 1 million in 1980, to over 1.5 million in 2000 and almost 2.5 million in 2014 (NCES, 2016). Asian American and Native American enrollment numbers have also increased over these decades, but not as extreme.

With the varying gender and racial composition of enrollments in undergraduate programs over time, came a need to also remediate this diverse population of students. “Student trends data suggest that critical differences persist across groups, with racial/ethnic minority students still lagging behind their Asian and White peers with respect to academic preparedness in mathematics upon college entry” (Pryor et al., 2006, p. 21). In their paper on the 40 year trends of American freshmen, Pryor et al. (2006) shared a summary of their results of a student survey regarding their own expected need for enlisting remedial tutor help in math. Across all ethnicities, there was a drop in reported impending need in 2005 compared to the survey results from 1971. White student perceptual need for mathematics remediation assistance dropped from 32.7 % to 20%, Hispanics fell from 54.9% to 38.5%, Black perceptions decreased from 56.2 % to 43.4%, American Indians 57.8% to 29.8% and Asian American sense of needing remedial mathematics help sank from 23.4% to 22%. In an annual report (ACT, 2015) on

the college readiness of the virtually 2 million students taking the ACT, the percent reaching a benchmark mathematics score, which indicated college readiness, varied between ethnicities. The percentages for this 2015 cohort meeting the requisite benchmark in math, thus not needing remediation, are listed here in descending order as follows: Asian (69%), White (52%), Hispanic (29%), Native American (20%), and African American (14%) (ACT, 2015). Subtract each from 100 to determine the percentages needing remediation. One may infer from these statistics that Asian and White students are more representative of being mathematically ready for college, as compared to the other ethnicities, however, no matter the gender or ethnicity, college remedial mathematics classrooms still do not discriminate.

As for postsecondary school graduation rates, all ethnicities saw an increase in degrees conferred at all types of higher education institutions between the 2002-2003 academic calendar year through the 2012-2013 year (NCES, 2015). Though there have been increases in diversity across American post-secondary schools, these graduation rates have not been equivalent for all ethnicities. The good news is the percent of Hispanic students receiving 2-year and 4-year degrees, has risen by over 120%, i.e., more than doubling during this decade (NCES, 2015). This increase may be due to more Hispanic students coming from households whose parents are both U.S. citizens. A study by Witkow et al. (2015) found third generation (both parents born in U.S.) Latino students persisted in college more than the second generation (only one parent born in U.S.), and significantly more than the first generation college student. The percent increase noted above is substantial, and the total number of certificates and 2-year degrees awarded for Hispanic students is larger than those of African American students,

however more Black students are receiving bachelor, master and doctoral degrees. Native American student enrollment in post-secondary schools remained one of the lowest populations. Their increase in degrees conferred did rise, as indicated in the NCES (2015) report, however their increase represented the smallest percent change.

Though these increases are encouraging one must not forget graduation rates for students requiring remediation have not been as promising. There are other characteristics besides ethnicity that help in painting a clearer picture of the mathematics students enrolled in remedial courses.

Parents Education. Another demographic research topic about remedial students, is that of the parent's highest educational attainment. An NCES (2012) report indicated that regardless of the academic calendar year, 1999-2000, 2003-2004, or 2007-2008, students whose parents attained only a high school diploma enrolled in a remedial course at the highest percentage rate, followed by parents with some postsecondary education. Students who had parents with a Bachelor's degree or higher, had the lowest remedial enrollment percentage rates during the 1999-2000, 2003-2004, and 2007-2008 calendar years. Success in these remedial classes may be predicated upon how far a parent's education went beyond high school. Research indicates parental education is a better predictor of student enrollment and success in college, than is family income (Choy, 2001).

In a 2013 paper by the College Board on ACT scores, the researchers studied the relationship of the parent's educational background and 6-year graduation rates of students not considered as being college ready (based on standardized test scores) (Mattern, Shaw, & Marini, 2013). The authors found a 6-year graduation rate range

between 45% for underprepared students with parents not having a high school degree to a high of 62% for parents attaining a graduate degree. For the students deemed college ready (based on standardized test scores), 6-year graduation rates were noticeably higher: 71% and 82% respectively for the lowest and highest parental educational attainment (Mattern, Shaw, & Marini, 2013). The 4-year graduation rates are much more alarming. Only 25% of the underprepared students with parents not receiving a high school graduated college in four years, while a mere 38% graduated in 4 years even though their parents had a graduate degree (Mattern, Shaw, & Marini, 2013). Based on this report, even before entering a postsecondary institution, the education of the parent(s) seems to effect standardized test scores, and these ACT or SAT scores in turn, are often used as a predictor for academic success in college. Some students, perhaps those whose parents have low educational attainment, may be at a disadvantage because of the level of education their parents have achieved. Students may not have gained from their parents, the necessary knowledge required to even apply for enrollment and financial aid, let alone enroll in classes, navigate through the campus, socially connect or seek assistance for that matter (Nelson, 2009). It may be imperative for teachers to discover the parental education attainment of each of their underprepared college student. Julie Nelson (2009), in a paper regarding the educational background of parents and its impact on their child's success, makes a case for why educators must ferret-out this information, more so for first-generation college students, if we are to help:

“As for first generation students may be especially susceptible to personal doubts regarding their academic and motivational ability. College-educated parents are typically more aware of the long-term benefits of acquiring a college degree, and thus they share this information with their children. The higher the degree the parents have obtained, the greater the support the student will have from their parents to complete a similar academic goal” (p. 5)

High School Mathematics and ACT/SAT. Academic success in high school, which may also be considered to be influenced by the educational background of the parent, is another predictor for success in college. Despite the background of their parent(s), many students do achieve success in high school, in part because of their own cognitive abilities. Looking back at high school academic achievement may help predict future college success. Postsecondary schools gather transcripts each year for the freshmen class, and also college-bound standardized test scores, which are often deemed equally important when forecasting a student's academic trajectory. Is one better than the other, in terms predicting future college coursework and success? Research seems to indicate there is no definitive answer.

For example, one study examining student's high school mathematics courses versus mathematics remediation in college, determined that students taking higher-level mathematics courses in high school required less remediation in college. These authors also found that too many students that did pass the higher-level mathematics courses unfortunately still required college remediation, thus they wondered if students were just passed along, or did the students not retain the material (Hoyt & Sorenson, 2001)? Another study, on the University of Wisconsin system between the years 2008-2010, concluded freshmen from the lowest quartile in high school rank comprised the largest percent needing mathematics remediation. This low performing group of students had the lowest academic achievement rate in their remedial mathematics course compared to the first, second and third quartile ranked students (Nook, 2013). Did these lowest quartile students have the cognitive ability to handle the material and tasks within the course? Successful performance on a cognitive task, requires "appropriate or correct

processing of mental information,” (i.e., have the necessary cognitive abilities) (Carroll, 1993, p. 10).

As for Standardized test scores like the SAT and ACT, there are also mixed opinions and research findings. First off, these are tests of aptitude, or the cognitive ability that is predictive of future successful learning (Carroll, 1993). The ACT organization conducted a large study on the correlations of high school GPA, SAT scores, and first year college GPA. The analysis determined there was a relationship between high school GPA and first year college GPA, a relationship between SAT score and first year college GPA, and even stronger correlation when considering high school GPA and SAT together (ACT, 2006). Relatedly, two other studies concluded student performance on college entrance exams, such as the SAT, are significant predictors of college persistence (Camara 2005; Titus 2004). More evidence that academic achievement and aptitude appear to be related

As for remedial mathematics students, Bettinger & Long (2005) concluded that students placed in a developmental mathematics course, had lower ACT scores and GPA's than those students in a college-ready course. In addition, their research showed a higher dropout rate for remedial mathematics students, 65.2% compared to a 30.8% dropout rate for non-remedial mathematics students, and subsequently a lower graduation rate, 18.1% versus 53.3% respectively (Bettinger & Long, 2005). On a couple of positive notes, the authors did surmise that the higher the remedial mathematics students ACT, the increased chance for a successful outcome in the class, and it was more likely for remedial mathematics students to graduate if they were in a math-related major (Bettinger & Long, 2005). The ACT is just one piece of data in a student's education profile, and

the ACT may be a good measure of how effective a student's education was, but it is not the definitive predictor for success in college, according to Jeff Nelson, CEO of OneGoal (Tough, 2012).

If educational assistance for all is a mantra for college and university remedial mathematics programs, then knowing even more details about these students including their work and family commitments can only help. There is no typical remedial mathematics student though so we may need to know more and we probably need to provide more assistance. McCabe (2000) agrees and claims it "is a good investment for society...and developmental educators need to continue their efforts to improve it" (p.17).

Work and Family. Two other potentially difficult circumstances that must be managed by 21st-century college students are working while attending college and family obligations. The percent of students working part time and full time has increased over the years irrespective of students being enrolled in college full time or part time. For 18-24 year-old college students enrolled full time, NCES (2009) reports a steady increase, from 1970 (just more than 30%) to 2000 (over 50%), in the percent of this population having a job while attending school. Additionally over those decades, there were substantive increases in the percent of students working 20-34 hours weekly and over 35 hours/week. Students working less than 20 hours per week remained steady between 1970 and 2005 as indicated by approximately 20% full time students were working those years (NCES, 2009). As for part time students, a consistent finding was reported, with about 80% of 18-24 year olds worked in 1970 and 2005, with a slightly higher percent in 2005 (NCES, 2009). When comparing community college students and students enrolled

in 4-year institutions, NCES (2006) reported nearly 80% worked while enrolled versus about 70%, respectively. NCES (2006) reports 41% of community college students work full time, with an average of 32 hours per week, while 23% of 4-year college-enrollees worked full time, with an average work week of 26 hours. An important issue to address is the academic advancement of the students who work a seemingly high average number of hours each week and those students working full time.

Research findings on the academic achievement of students being employed, varies on whether it is full time work, part time, on-campus or off. According to Furr and Elling (2000), almost 30% of students working full time, unfortunately admitted work often negatively influenced their academic advancement. Working full time can affect attendance, dedication to homework, preparing for tests and socialization. According to Chen (2007), if a student is working full time, they likely are part-time students, and part-time students persist less and graduate at a lower rate as compared to students enrolled full-time. Only 7.8% of the students enrolled part-time at 2-year schools graduate in four years, while a mere 24.3% of students enrolled part time at 4-year institutions graduate in eight years, compared to 60.6% of the 4-year full time students (CCA, 2012). Of note, there was no research found indicating a general trend of full time workers out-performing academically, their part time working peers.

As for part time workers while in college, the research on the influence it has on student achievement varies. Some research suggests it may depend on the number of hours worked. There may be a certain limit on the hours worked that precludes negative effects on student academic performance. “The threshold model posits that student employment is harmful only if a student works an excessive number of hours” (Tessema,

et al., 2014, p. 53). Their research on the academic achievement (GPA) of over 5,200 seniors at a Midwestern university found that students working 1-10 hours per week had the highest GPA. The GPA's descended as hours increased in order from the 11-20 hours per week, to 21-30, and over 31 hours per week (Tessema, et al., 2014). Similar results were found in a study of nearly 7,000 students enrolled in a Minnesota university, where the analysis concluded that for the students who worked, they realized a 0.004 decrease in GPA, for each additional hour worked each week (Wentz & Yu, 2010).

Other research claims it may further depend more on whether the job is on- or off-campus. One study at a prestigious urban university reported first and second year students who worked on campus part time, graduated at a higher percentage than the off-campus workers (Cermak & Filkins, 2004). The study by Furr & Elling, (2000) might help explain this statistic for they claim working off-campus lessens the interactions with faculty which may decrease the critical learning experiences on campus. Many non-traditional students commute to college and do work off campus. Having a conversation about how to manage part time or full time work, and schooling can only take place if teachers learn of the work schedules and locations of their students. Non-traditional adults comprise an important sector of remedial students, which stresses this need for communication between teacher and student.

Not only do students who are underprepared have to work extra hard on mathematics to come up to speed, they may also have to hold a job while in college to help pay for school, compounding the time management struggle. Astonishingly, more than 25% of all U.S. undergraduates are raising children while enrolled in school (Gault, et al., 2014). This report also details that of the approximate 4.8 million college students

who are parents, over 70% are mothers, the balance being fathers, and noteworthy is that over 2 million of these students are single mothers. Of concern also in their data is the report that 88% of single parent college students are at or below the poverty line (Gault, et al., 2014). For some, balancing family obligations, a job, and college academic is increasingly difficult. Berkner et al., (2002) claimed being married, tending to children or siblings, and especially being a single parent, may be a serious determinant to college persistence. Gault et al. (2014) reported the majority of parents spend 30 or more hours each week tending to their children while also going to college. Unfortunately as a result, only one-third of students who are parents ever complete their degree within six years (Gault, et al., 2014).

Performing time-management and cost-benefit analyses regarding academics, full or part time work, family obligations and the need for ‘down time’ may be difficult for non-traditional students, and maybe even more challenging for first-generation freshmen. These type of students are most at risk of not completing their degrees, so understanding their obligations are essential if improvements in graduation rates are in order. Faculty members can help students who are least-prepared and whose hectic lives must be juggled, if they can learn about those challenges.

Also, part of this improvement may entail understanding other aspects of the remedial students in classrooms across the country. Besides their demographic makeup and cognitive abilities, discovering their non-cognitive and metacognitive characteristics may also help. Do non-cognitive factors such as grit and mindset or metacognition contribute to the academic success of college students? Determining their mindsets about their mathematics ability, the level of grit they exude while doing their mathematics

work, and their awareness of their own metacognition, may help teachers develop environments that advance student learning and perhaps subsequent academic success including graduation.

Mindset, Grit and Metacognition

Research (e.g. Duckworth, & Seligman, 2005; Dweck, et al., 2011; Heckman & Rubinstein, 2001; Young & Fry, 2008) indicates that non-cognitive traits such as mindset and grit along with metacognitive awareness may be important contributors to student success in the classroom. Thus, this section will include a discussion of literature on mindset, level of grit, and metacognitive awareness.

Mindset. The Merriam-Webster dictionary defines mindset as a “mental attitude or an inclination” (m-w.com, 2011). Dweck (2006) asserts that mindset is a self-perception or self-theory that people adopt. When considering the self-perception of oneself, Dweck professes people have deep-rooted or implicit theories of themselves. For example, people have self-theories of their own personality, musical or athletic ability, and/or intelligence. Dweck and Leggett (1988) identified two specific implicit self-theories: an entity theory whereby people believe an attribute or ability is fixed or unchangeable, and an incremental theory whereby people believe an attribute or ability can improve or change. Some people have one general theory of their selves, but not typically across all attributes (Dweck, Chiu, & Hong, 1995). One may, for example, possess an incremental theory regarding athletic ability if one feels with practice their skill level can improve, while also possessing an entity theory regarding intelligence, for they feel they are smart or not smart.

An incremental theorist, is considered to have a growth mindset, or incremental theory of intelligence, and believes intelligence can increase or grow with effort (Dweck, 2006). Students endorsing a growth mindset believe that their ability to learn or increase their intelligence, can occur through effort. Exerting effort is not seen as an inability to learn, but an opportunity to grow and learn. Blackwell, Trzesniewski, and Dweck (2007) found students who believed in the incremental theory of intelligence accepted challenging tasks because they help promote skill development. Failures also do not deter students with growth mindsets, and with these failures, they ask for accurate assessment of their ability in order to correct or improve them (Dweck, 2006).

Entity theorists, possess a fixed mindset, or an entity theory regarding intelligence, however, and believe their intelligence cannot increase (Dweck, 2006). Students with a fixed mindset, having the notion that intelligence is invariable, are performance-goal oriented. Demonstrating knowledge and gaining positive recognition is valuable and important to entity theorists (Hong, et al, 1999). For students with a fixed mindset, failure is a setback which confirms they are not smart enough or talented enough (Dweck, 2006). They give up easily when effort is required, or a negative outcome is imminent (Blackwell, et al, 2007). Students with fixed mindsets try to avoid demonstrating insufficient or inadequate cognitive abilities, and explain their struggles by iterating a lack of natural intelligence in that domain. To entity theorists exerting effort is an indication of a lack of ability or intelligence (Dweck & Leggett, 1988).

One mindset or implicit theory is not better or more correct than the other (Dweck, Chiu, & Hong, 1995). In fact “prior to receiving negative feedback, the intellectual task performance of entity theorists, as a group, is entirely equivalent to that

of incremental theorists” (p. 273). Albeit, the mindset one holds may have considerable effect on a student’s performance when difficulties arise (Dweck, Chiu, & Hong, 1995).

Performance-goal oriented students have a fixed mindset (Dweck & Leggett, 1998). Students with performance-goal orientation want to show or prove their abilities, but “avoid giving evidence of inadequacy” (p.259). Their effort wanes when challenging tasks are given. Avoiding risks and low persistence are indicative of these students. Their focus is on adequacy of ability, receiving positive judgments and avoiding negative ones regarding competence. Conversely, students who are learning-goal oriented focus on the development of their ability. Seeking challenges and persisting through them helps increase competence and improves intelligence, which are characteristics of a growth mindset (Dweck & Leggett, 1988). Whether performance- or learning-goal oriented, Dweck & Leggett (1988) conclude implicit self-theories are predictors of children’s goal orientation. They suggest an implicit theory-goal orientation-behavior formulation exists during achievement situations. Based on the orientation of their goals, student’s exhibit patterns of behavior, these patterns are observable and align with an implicit theory.

Understanding the mindset of an individual helps predict behavior. Research on mindsets or implicit theories and academic performance have been the focus of studies involving children, middle and high school students, and college students.

In *Mindset: The New Psychology of Success*, Dweck (2008) wrote about her early research which focused on how children coped with failures, and how the praise people offer these children along the way, effects them later in life. She determined that praising children as being smart, i.e., for getting an answer correctly quickly, leads a child down

the path of a fixed mindset. On the other hand, praising a child for toiling through their work, leads a child toward a growth mindset.

Other researchers joined Dweck in collaboration, and still other individual researcher(s) separately, studied the mindset of older-aged school kids. In terms of middle school aged students, research results (Blackwell et al., 2007; Henderson & Dweck, 1990) indicated sixth and seventh graders who adopted an incremental theory of intelligence achieved academic success, with even low-performing students with a growth mindset improving academically the next year, and out-performed their fixed mindset counterparts. Contrarily, middle school students with an entity theory of intelligence tended to continue to receive low grades in seventh grade as well. These fixed mindset students also reported more negative feelings about schoolwork. The mindset of the student predicts behavior regardless of a student's gender, ethnicity, or socioeconomic status. One study (Good, Aronson, & Inzlicht, 2003) focusing on female, minority and low socioeconomic middle school students, concluded students who were given a growth mindset-like written letter of encouragement (intelligence can grow was the theme) from college students, had significantly higher achievement scores than those students receiving a written note that achievement is based on educational setting. The researchers determined female, minority and low socioeconomic students with a growth mindset performed as well as their Caucasian peers.

As for high school, studies have also found growth mindset students academically outperform their fixed mindset peers as well (Claro, Paunesku, & Dweck, 2006; Jones, et al., 2009; Devers, 2015). Devers (2015) mindset study included AP Physics high school students and ten college students in an upper-level physics class. After attempting a

mindset intervention, she determined no significant mindset changes amongst both sets of Physics participants. The researcher did find a moderately strong correlation between change in mindset and academic growth for the high school Physics students only. For the college Physics students no correlation between change and academic performance were determined.

Other studies regarding the mindset of college students involved African American versus White students, STEM, Computer Science and Engineering undergraduates (Aronson, et al., 2002; Good, Aronson, Inzlicht, 2003; Murphy & Thomas, 2008; Stump et al., 2009). Results indicated African American students encouraged to view intelligence as malleable, performed as well academically as their white peers, while students not receiving the same encouragement, underperformed comparatively (Good et al., 2003). STEM students with a growth mindset outperformed academically, and worked through failures, unlike the fixed-minded students, whom struggled to recover after a poor grade (Dweck, 2003). Mixed results were found, engineering students at a large university students had varying beliefs about the malleability or fixed-nature of intelligence, and their mindset perceptions did not predict course grades. The authors did find however that students who believe intelligence can grow, exhibited more active and collaborative knowledge building behaviors, compared to entity theory students (Stump et al., 2009). Murphy and Thomas (2008) believe there is an impending need to conduct mindset research on college Computer Science students, since computer programming errors produce a stopping point. At this moment, how setbacks are handled by the programmer, may indicate a growth, or fixed mindset. The authors cite Perkins et al. (1986) who refer to “stoppers” as computer programmers who

give up because of their perceived inability to make the program work. Murphy and Thomas (2008) equate this to having a fixed mindset. Oppositely, “movers” (1986) are students who debug and subsequently modify the code, to get past the initial setback. Murphy and Thomas (2008) equate this to having a growth mindset. Though their study has not taken place as of 2016, it still may be pending.

In terms of mathematics, Dweck (2008) states “students have more of a fixed view of mathematics” (p. 2); therefore researchers have studied the ability to and effects of changing to a growth mindset. Burkley et al. (2010) predicted and proved, women undergraduates having a fixed view of mathematics, were more disengaged with the subject matter, and were less interested in math-related courses and careers, than those adopting a growth mindset. Likewise, Good, Rattan and Dweck (2007a) determined female calculus students with fixed mindsets, experienced a decrease in grades throughout the semester, and less of an interest in mathematics courses in the future. The growth mindset students experiencing the same negative sense of belonging in Calculus, persevered, received good grades, and planned to continue taking mathematics courses.

Sriram (2014) studied the effort and academic achievement of at-risk college students. At-risk refers to students needing remediation their freshmen year in college. One-hundred and five first-time underprepared students received either a mindset intervention or a study skill intervention. Results indicate post-intervention, significantly more students changed to a growth mindset after the mindset intervention, than the study-skill group. The achievement level between the groups were not significantly different despite an increase in reported effort by the mindset intervention group. Robins and Pals (2002) determined the mindsets of the 508 college students in their study, did

not significantly change when moving from high school to college, which unfortunately signify student self-theories of intelligence likely remain stable.

Boaler (2013) believes fixed mindsets contribute to “inequalities in education” and also to students’ “low achievement and participation” (p. 150). As such, the research on mindset discussed above, underscores the importance of determining students’ perceptions and experiences. To determine perceptions of the malleability of intelligence, the researchers noted above utilized variations of an Implicit Theory of intelligence scale. For example, Devers (2015) used a 16-item likert-type questionnaire developed by Dweck in 1999. Half of the statements were fixed mindset phrases and the other growth mindset statements. Blackwell et al (2007) and Stump et al (2008) used Dweck’s (1999) 6-item questionnaire. On this Implicit theory of intelligence scale, there were three entity theory statements and three incremental theory statements, for which students were to disclose their agreement to the statements, based on a 6-point likert-type scale. Other researches (Sriram, 2014; Burkley et al. 2010) utilized the 3-item likert-type instrument developed by Dweck et al (2005). Since this scale is only 3-items, and since implicit theory is a “construct with a simple unitary theme,” Dweck et al. (1995) felt including both entity type and incremental type phrases would add to the confusion and boredom of participants. Burkley et al. (2010) also used a modified, mathematics specific, version of the 3-item Implicit Theory of Intelligence scale. A sample statement was “Your math aptitude is something about you that you can’t change very much” (p. 236). Additionally, a two-item Self theory of Intelligence was utilized by Aronson, et al. (2002). The two items were “you have a certain amount of intelligence and you really

can't do much to change it"; and "you can learn new things, but you can't really change your basic intelligence" (p. 118).

Understanding the mindsets of these students may be important, since academic transitions, such as the transition to middle school, high school, or college are uncharted educational experiences for them. Determining other student characteristics, like grit and metacognitive awareness have also been studied by researchers. Dweck (2012) for example believes that one way students learn to become gritty is to embrace a growth mindset – a mindset that allows individuals to use failure as an opportunity for reflection instead of an opportunity to quit.

Grit. Grit, as defined by Duckworth et al. (2007) is "perseverance and passion for long-term goals" (p. 1087). Thus, their construct has two components: perseverance and passion. Perseverance entails maintaining effort through challenges, failures, and plateaus, while in pursuit of reaching a goal. It is about sustaining effort and the stamina one exudes in order to accomplish anything worthwhile (Duckworth & Eskreis-Winkler, 2013). Duckworth et al. (2007) proclaim grit is not only about perseverance over time, but also passion over time. In an interview on resilience and learning, Duckworth says "grit is not just having resilience in the face of failure, but also having a deep commitment that you remain loyal to over many years" (as cited by Perkins-Gough, 2013, p. 16). Passion for a long-term goal, therefore refers to a consistent interest, maintained over years, toward achieving a goal. Grit is more than just self-control, it also requires an unswaying and enthusiastic dedication to achieve a long term goal (Tough, 2012).

The seed that led Duckworth to develop her notion of grit, began when Duckworth could not conceptualize why her own middle school math students, that had equal intelligences, had varying levels of success. Through grade calculations, she determined that higher IQ students in her class, did not have the highest grades, in fact some lower IQ students had higher grades. As a result of this phenomena, the big question she set out to answer was “Who is successful and why?” (Duckworth, 2013). To begin to help answer her question, Duckworth et al. (2007) interviewed engineers, bankers, lawyers, and other professionals to determine the qualities of successful individuals in those respective fields. The interviewees consistently used words synonymous to grit, i.e., zeal and hard-working, as often as they used words synonymous to talent; implying talent was as important as grit.

Honing in on this notion of persistence or steadfastness, Duckworth and her colleagues (2007) subsequently, analyzed decades of research studies on concepts like grit and talent, including 19th century research on distinguished artists, scientists, and statesmen, through a 1940’s study of doctors and lawyers, to the 1980’s study on personality traits. Their synthesis of this research revealed concepts like strong devotion, intensive labor, perseverance and conscientiousness, were characteristics of successful individuals, and predictors of success. An example of one conclusion drawn from their synthesis was “conscientious individuals are characteristically thorough, careful, reliable, organized, industrious, and self-controlled” (p. 1089). While conscientious individuals may perform a task diligently, they may not maintain long term interest. Duckworth et al. (2007) then conjectured that grit may differ from conscientiousness based on duration required to accomplish a task and also the sustained interest to achieve a long term goal.

Duckworth et al. (2007) embarked on a series of six studies with the goal of creating a valid and reliable instrument that measures their concept of grit, as well as test the conjecture that grit is predictive of success or achievement, and that grit is different than conscientiousness. Their seminal research commenced with an initial group of adults over 25 years of age, utilizing a 27-item questionnaire aimed at determining the “attitudes and behaviors characteristic of high-achieving individuals” (p. 1090). After statistical and factor analysis of the original 27-items, the 12-item grit scale was developed and used to measure the grit of this initial group of adult participants.

Results of this first study indicated older adults were grittier than their younger peers, and adults with more education, were grittier than those with less education, which impelled Duckworth et al. to study other groups with the 12-item grit scale (2007). Their continued research resulted with the following: Ivy-league students with higher undergraduate GPA's had higher grit scores, than those with lower GPA's, however surprising to them, the authors found that participants, from this elite university, with lower SAT scores were grittier than those with higher SAT scores, perhaps suggesting weaker students must work harder than their brighter peers. Additionally, the researchers determined cadets higher in grit were more likely to complete summer training, grittier Spelling Bee contestants went further in the competition than their less gritty peers, and grit was a better predictor of success than the Big 5 personality trait of conscientiousness (Duckworth et al., 2007)

This original 12-item Grit Scale (Grit-O) developed by Duckworth, et al. (2007), intended to test perseverance coupled with consistency of interest, and the predictive ability of this sum, with respect to achievement and/or success. In light of the

development of the grit scale, and informative results, other researchers utilized the instrument to study a variety of groups and a variety of measures of success. Two example studies include the grit of women lawyers (Hogan, 2013), and the grit of fourth – eight graders in Southeastern elementary and middle schools (Rojas et al., 2012). The results of these two studies showed grit had a statistically significant strong relationship with hours worked by female lawyers, and with the type of workload/cases they were given (Hogan, 2013). Rojas et al. (2012) had over 2,400 fourth-eighth grade students self-evaluate their levels of grit, self-efficacy in mathematics and reading and self-regulation in mathematics and reading. The researchers determined a positive correlation between all three measures (grit, self-efficacy and self-regulation), and also girls had higher grit scores than boys.

The published Chronbach alphas for the original 12-item grit scale tested in studies by Duckworth et al. (2007), were .84, .78, and .85 for Part 1 - Consistency of Interest, Part 2 - Perseverance of Effort, and total grit score, respectively. In this foundational study, though calculated, the researchers did not test each factor, perseverance of effort and consistency of interest, individually for their outcome predictive ability on the original grit scale. Duckworth and Quinn (2009) examined whether a shorter version of the original grit scale, having four less items, had improved reliability and validity, while retaining the original factors of perseverance and consistency of interest. To confirm the two-factor model and predictive nature are preserved, and to validate this new scale, Grit-S, these authors performed a series of studies, some of which included similar participants used during the validation of the Grit-O, original grit scale. Duckworth and Quinn (2009) surmised, Grit-S is valid, it

maintains the two-factor model, and the factors, perseverance and consistency of interest were distinct from each other, though reliabilities were somewhat lower ($\alpha = .73, .60,$ and $.73$ for Part 1, Part 2, and total grit score respectively). Their study using the 8-item Grit-S predicted successful completion of summer training for West Point cadets, predicted advancement in a national spelling bee contest, were significantly associated with age for participants 25 years old and up, GPA for secondary school participants, and inversely to hours watching TV for the same group, and inversely to the number of career changes of adults. In terms of the individual predictability of each factor, Perseverance of Effort was a better predictor of GPA, than Consistency of Interest and total Grit-S score, while Consistency of Interest was a better predictor of spelling bee contestants and career changes (inversely), than the total score and Perseverance of Effort. Total Grit-S score was a better predictor of cadet retention, than the individual factors.

Other studies utilizing the Grit-S scale have been conducted on male African American students in a predominantly white institution (Strayhorn, 2013), freshmen students at a highly selective university (Chang, 2014), novice teachers at low-income public schools (Duckworth, Quinn & Seligman, 2009), nursing students (Robinson, 2015), and urban 9th and 12th grade high school students (Gorman, 2015). Results of these studies indicate grit had a positive association with the grades of black male students. Grittier African American students at the predominantly white public university had higher college GPA's than their peers (Strayhorn, 2013). The Perseverance of Effort subscale of Grit-S was a significant predictor of freshmen GPA at a southern highly selective university (Chang, 2014), while novice teachers highest in total Grit-S score at low-income public schools, were more effective teachers as measured by their student's

academic gains (Duckworth, Quinn & Seligman, 2009). Robinson (2015) determined grittier nursing students were more engaged in participation and interaction with the teacher and with classmates both inside and outside of classroom, and student engagement predicted academic achievement. The grittier students reported more active participation in small-group class discussions, raising their hands and asking questions when they did not understand and meeting with the professor to ask questions or review assignments outside of class (Robinson, 2015).

Gorman's (2015) dissertation used the Grit-S scale to measure the grit of urban high school students, but also examined who influenced the grit of these students, if at all, and where students learned or experienced grit, as well questions on college aspirations and self-reported grades. Gorman concluded seniors were grittier than freshmen, and higher grit scores were associated with college aspirations and self-reported grades.

Regardless of which of the two instruments, Grit-O or Grit-S, were utilized in research, both consistently indicated gritty individuals finish tasks, achieve more and maintain interest in a larger pursuit of a long term goal. Obstacles along the way of achieving the long-term goal, do not impede individuals high in grit.

Non-cognitive skills like grit are now considered equally important as IQ, when considering academic success and career employment (Tough, 2012; Gutman & Schoon, 2013). Though studies on grit involving university students have been conducted, no literature has been found specifically studying first-time freshmen enrolled in all levels of mathematics, from remedial mathematics through calculus.

Metacognitive Awareness. Before defining Metacognitive Awareness, one might begin with understanding metacognition. Some researchers (Doyle, 2013; Memnun,

2013; Mokhtari & Reichard, 2002; Mytkowicz et al., 2014; Panaoura & Philoppou, 2003; Sperling et al., 2004; Teo & Lee, 2012) conclude that the concept of metacognition may have been introduced by Flavell, who referred to it as the knowledge and cognition about one's cognitive experiences, and the "active monitoring and consequent regulation and orchestration of these processes" (1979, p. 232). Since Flavell's initial declaration, other researchers have continued to define or redefine metacognition. In the ensuing decade since Flavell, Brown (1981) for example, indicated metacognition entails understanding and controlling thinking during cognitive routines, while Cross and Paris (1988) consider metacognition is about having the knowledge and control of one's thinking. Even more recently, Paris and Winograd's (1990) idea of metacognition involved self-appraisal and self-management, while Everson and Tobia (1998) suggest it consists of accurate monitoring in order to adjust learning strategies and goals. Metacognition ascribes to one's ability to think, reflect, self-interrogate, rethink, and persistently monitor ones understanding and mastery of knowledge (Bransford et al., 2000).

From these various ideas, there appears to be a theme about metacognition, namely there is an understanding of how one learns (a knowledge) and that monitoring and regulation are key elements. Metacognition refers to the ability to continuously think about one's thinking. Schraw & Dennison (1994) believe metacognition is comprised of two main components: knowledge of cognition and regulation of cognition.

Knowledge of cognition refers to what the student knows about their own learning, including knowing how they learn, strategies or methods they know, and the conditions in which to use certain strategies. Schraw et al. (2006) claim that knowledge of cognition is comprised of three subcomponents: declarative, procedural, and

conditional knowledge (see Figure 2). Declarative knowledge means knowing strengths and weaknesses of one's intellect and skill set, including both general factual knowledge and ability to memorize information and strategies. Procedural knowledge calls for awareness, application, and management of cognition. It is about knowing how a strategy, procedure, or method would be useful during a task (Schraw, 1998).

Conditional knowledge refers to knowing when, where and why to use a particular learning strategy (i.e., under what conditions will a strategy be effective) (Thomas & McRobbie, 2001).

The second component of metacognition is the regulation of cognition (Schraw & Dennison, 1994) when put simply, it refers to how well students control and govern their own learning. These authors divided regulation of cognition into five subcomponents: planning, information management strategies, monitoring, debugging, and evaluation of learning (see Figure 2). Planning involves goal setting, strategy selection, and pacing or time management (Schraw & Dennison, 1994; Schraw et al., 2006). Information management strategies according to Schraw and Dennison (1994) involves selective focusing, organization, summarizing, and processing of information in order to successfully manage the task at hand. Monitoring is the periodic, yet constant, self-evaluation of comprehension and task performance, including whether the strategies are correct and/or implemented correctly. During the monitoring phase, the debugging subcomponent is activated when students are regulating their cognition. Debugging strategies are used to correct comprehension and performance errors (Schraw & Dennison, 1994). Lastly is evaluation which includes analyzing the effectiveness of

one's learning or comprehension, performance or strategies used during the learning process (Schraw et al., 2006).

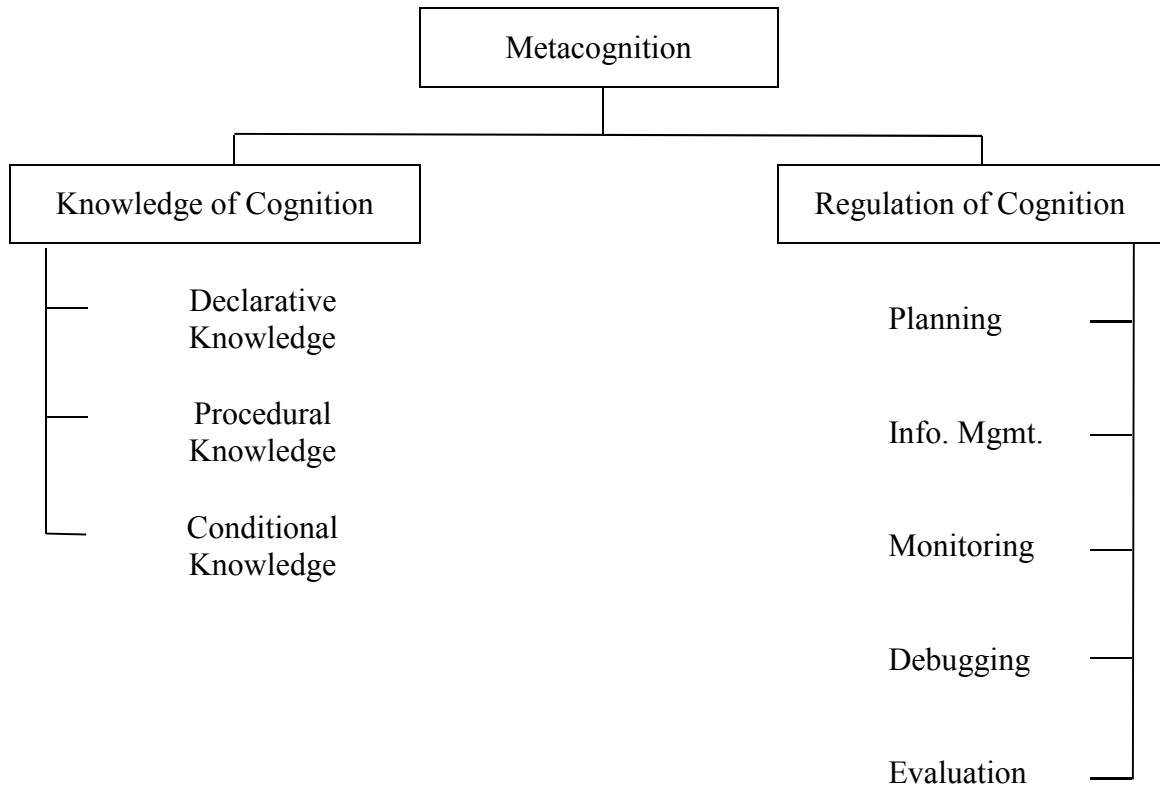


Figure 2. Metacognition and its Subcomponents. Adapted from “Assessing Metacognitive Awareness” by G. Schraw and R.S. Dennison, 1994, *Contemporary Educational Psychology*, 19, p. 474.

Knowledge and regulation of cognition are individual subcomponents of metacognition, yet they overlap and students who exhibit both, have metacognitive awareness (Schraw & Dennison, 1994). Metacognitive awareness thus is being aware of ones metacognition. When students have a sound metacognitive awareness about their learning, they are able to gauge their current progress, continuously determine better

strategies to meet the ever-changing and higher goals, i.e., develop adaptive expertise. Having metacognitive awareness is vital for success in learning because it affords students the ability to manage skills in order to develop better skills (Bransford et al. 2000). “Metacognitive skills include a range of behaviors that reflect greater student self-awareness, self-monitoring, and self-control—study skills, work habits, time management, help-seeking behavior, and social problem-solving skills” (Roderick et al., 2009, p. 190).

While teachers may know the various levels of student pre-existing content knowledge, including recognizing the proficiencies and deficiencies of each individual, educators must also become familiar with their thinking strategies, before improvement in content knowledge and ability can take place. “There is good evidence that learning is enhanced when teacher’s pay attention to the knowledge and beliefs that learners bring to a learning task, use this knowledge as a starting point for new instruction, and monitor students’ changing conceptions as instruction proceeds” (Donavan & Bransford, 2005, p. 11). This suggests that both teacher and student are monitoring and controlling thoughts, which falls within this lens of metacognition.

One of the instruments developed to aid educators, and students alike, in determining and assessing metacognitive awareness is the Metacognitive Awareness Inventory (MAI) which was developed by Schraw and Dennison (1994). There are other methods of determining awareness of student metacognition, like talk and share, observations of students work, and one-on-one or small group interviews, which often take place during an in-class setting (Veenman et al.,2005). These methods are limited since one can only assess small numbers of students at a time. Questionnaires or surveys

on the other hand, like the MAI, can reach a larger population of students, may afford the participants anonymity so as to answer more honestly, and can provide the researcher with quick data for evaluation purposes (Tobias & Everson, 1996; Pintrich & DeGroot, 1990).

Schraw and Dennison's MAI assessment tool consists of a 52-item statements representative of the three subcomponents under knowledge of cognition and the five subcomponents under regulation of cognition (see Figure 2). Research participants respond to each statement, using a 5-point likert-type scale, ranging from (5-*Very true of me*, to 3-*neutral* to 1-*Not at all true of me*). If the statement does not reflect one of these three responses, participants select 2 or 4 revealing a "more or less like me" indication. Each item on the instrument is a statement about one's knowledge of how they learn or of the actions one must take to regulate their learning. A knowledge of cognition, regulation of cognition and a total metacognitive awareness score will each be determined by adding up the points. Higher scores indicate more knowledge of cognition and greater metacognitive regulation, and in combination the more metacognitive awareness one has. In their seminal work, with undergraduate educational psychology students during the development and testing of the Metacognitive Awareness Inventory (MAI), Schraw and Dennison found the instrument to be both valid and reliable with an overall Chornbach alpha of 0.95, with similar sub-scales Cronbcach alpha's of 0.91 for both knowledge of cognition and regulation of cognition (1994).

As a result of this established instrument, researchers used the MAI, or modifications of it, to study a variety of populations regarding how metacognitive

awareness is associated with other variables, such as grade point average, course grades, gender, age, confidence judgments, and rubric development.

Studies with education majors and teachers were common, likely because teachers are “expected to model and teach cognitive and self-regulatory functions to their students. The ability to self-regulate and teach students how to self-regulate and self-assess, is predicated on *self-awareness*” (Pucheu, 2008). Young and Fry, for example (2008) concluded the MAI of upper level college of education students correlated with their GPA’s and course grades, yet there were significant differences between the undergraduate and graduate groups. Memnun (2013) compared United States pre-service teachers to Turkish pre-service student teachers and found similarities in total metacognitive awareness, though he concluded there were significant differences within the subcomponents of knowledge of cognition and the subcomponents within regulation of cognition. American student declarative and procedural knowledge, as well as debugging strategies were found to be higher than the Turkish students (Memnun, 2013). In a study of MAI and its relation to motivation and performance of college students in an Introductory Educational Psychology course, Hammann and Stevens (1998) determined knowledge of cognition was related to student academic performance and motivation, while being negatively correlated with test anxiety. The researchers also determined regulation of cognition was correlated to strategic components of the Motivated Strategies Learning Questionnaire (MSLQ). Sperling et al. (2004) used educational psychology sophomore and junior college students in part-2 of their study of MAI and student accuracy of confidence judgments. Students predicted their accuracy on each of 20 objective questions prior to answering them. After the test students re-predicted their

correctness, after which accuracy (percent correct) was determined. The authors concluded metacognitive awareness was not positively related to student accuracy of confidence judgments. Pucheu (2008) studied how metacognitive awareness was associated with high school teacher's ability to use scoring rubrics appropriately. The author determined teachers who successfully used scoring rubrics, had higher metacognitive awareness, and as a result, faculty development was not necessary.

Other collegiate-level MAI studies reviewed included students in nursing, introductory psychology, remedial chemistry, and freshmen college strategy courses. Doyle (2013) researched the metacognitive awareness of students in a pre-nursing program. She found no correlation between MAI and age or GPA. After an intervention though the participants had a significant increase in knowledge of cognition, however regulation of cognition and total metacognitive awareness did not significantly increase. Rincon-Gallardo (2009) studied whether the use of learning journals in an introductory psychology course had an effect on metacognitive awareness levels and academic achievement, versus students who did use a journal. The author concluded the journals positively affected metacognitive awareness, however the achievement levels between the two groups were not different. Interestingly the author also found a positive relationship existed between the father's educational attainment level and metacognitive levels. Students in a remediated chemistry class, received metacognition and motivated learning tutelage, and subsequently realized similar academic achievement levels as students not requiring remediation (Hesser, 2015). As for students in a college strategies course, Sperling et al. (2004) determined an inverse correlation between the credits dropped by freshmen enrollees, and their MAI scores, which may indicate students who

are metacognitively aware understand how to learn successfully, thus are retained. Additionally the authors concluded there was a positive correlation between the MAI and the Learning Strategies Survey which examines the frequency and types of strategies used, and their relationship to academic achievement. In another study of college strategy students, Mytkowicz, et al. (2014) found freshmen learning disabled and ADHD student metacognitive awareness scores increased from first to second semesters, and that the second semester scores were significantly correlated with GPA. Burchard & Swerdzewski (2009) studied college students in strategic learning course, and realized similar results as Mytkowicz et al., yet also found learning disabled students increased metacognitive awareness just as students without disabilities did. Additionally, though the initial scores for the disabled group of students enrolled in the course were low, their metacognitive regulation ended up being significantly higher than the general population of students not enrolled in the course. “Importantly, the much lower starting rate at which course participants used strategies to regulate learning gives additional evidence that the strategic learning course provides students with a powerful and beneficial learning experience” (p. 30).

As for the review of the literature on the metacognitive awareness inventory (MAI) in the field of mathematics, research seemed limited. Studies involving elementary and high school students, pre-service elementary mathematics teachers, and college differential equation mathematics students were initially found and reviewed. Sperling et al. (2002) constructed the Jr MAI, a modification of the MAI, and tested this version which was intended for assessing the metacognitive awareness of primary school aged children. Results indicated this adapted instrument was correlated with the original

MAI, however correlations between achievement and Jr MAI were small and not significant. Reed (2015) determined high school pre-calculus students who took the MAI three times (once every three weeks) increased their awareness scores afterwards, but more importantly had significantly higher grades in the course than the students not taking the inventory. Memnun and Hart (2012) used a Turkish version of the 52-item MAI to study the metacognitive awareness levels of mathematics teacher-trainees at a university in Turkey. Results indicated a small positive correlation between the regulation of cognition and student GPA's. However, the researchers found no correlations between metacognitive awareness and either gender or class standing (freshmen, sophomore, etc.) In the upper-level college mathematics class study involving differential equation students and the predictive nature of metacognition on course performance, Smith (2013) used a subset of the MAI, focusing specifically on the declarative, procedural and conditional sub-components of the knowledge of cognition category. Though the researcher found differences in metacognitive awareness based on grades, the fact that "D" students had higher MAI scores than "C" students, yet "B" students scored higher than both, indicated metacognitive awareness scores do not predict higher academic performance.

Research on the MAI of remedial or developmental mathematics students in college could not be located, however research using another means to assess metacognition was found. Bol et al. (2015) studied academic achievement levels in relation to metacognition using the Motivated Strategies for Learning Questionnaire ([MSLQ] scale. The experimental group received self-regulated learning training and practice during their developmental mathematics class, while the control group did not.

Based on final exam results of the two groups, the researchers concluded metacognitive regulation and achievement scores were significantly higher for the experimental group. Review of the literature stopped after finding no MAI research with remediated mathematics student participants.

Based on the plethora of research on metacognition though, determining, and understanding student thinking seems to be of critical importance. For teachers, gaining this information may help guide instruction and steer the class toward mastering the requisite learning goals. Teachers must continue to support student metacognition development because students can become engaged in the all of their learning endeavors (Donovan & Bransford, 2005), and “students learn more and learn better when they take control of their learning by defining goals and monitoring their progress” (NCTM, 2000). When a student can monitor, debug, try new strategies, and reflect, they develop a valid self-assessment of their own work. When students develop metacognitive skills like these, they are developing the ability to become their own teacher, i.e., teach themselves (Bransford et al., 2000). Though one cannot conclude definitively that there is relationship between metacognition and any specific variable for all students, the goal of all educators should still be to provide help to student learners, yet also cultivate independent self-sustaining students (NCTM, 2000) who can use metacognitive awareness to meet their own goals.

Summary

The cost of college remediation is not inexpensive, and the fact that remedial students continue to fail their courses, and subsequently drop out, has been and remains

to be an enormous concern for higher education institutions. A 2008 study indicates public colleges in America spent more than \$2 billion each year on remedial courses (Strong American Schools, 2008). A 2012 indicated a much higher cost of \$6.7 billion annually, which is why there continues to be a need to research and ultimately improve success rates in these courses and graduation rates of students needing remediation. Remediation plays an increasingly important role in the lives of the diverse group of students attending the various colleges and universities in America. In Oklahoma, the setting for this study, not all post-secondary schools have the same demographic make-up, use the same placement tests and procedures, nor provide identical remedial courses, sequences, instructional modes, nor define and determine success consistently. As Calgano and Long (2009) suggest “two students with the same characteristics face dissimilar probabilities of remediation if they attend different schools” (p. 4). With national sentiments like this, there are growing debates about how effective remediation is, how it should be delivered, and what student characteristics may be important for success.

With the high costs of attending college still increasing for *all* students, having a job while in school is not a choice for many of the college students of today. Non-traditional students attending college may also be burdened with family responsibilities. Teachers must determine the family and work obligations of their students in order to help them learn how to be successful in the class. Gaining a historical understanding of their high school academic records, including SAT/ACT scores, and even the parents educational attainment can also paint a portrait of each student. “Students’ beliefs about their academic ability influence their academic tenacity” (Dweck et al., 2011, p. 5).

Therefore determining student mindsets, levels of grit, and awareness of metacognition fills in more of the picture.

Teachers who want to have a positive effect on the success of their students, need to really know them so they can provide the necessary resources. In *How Children Succeed* by Paul Tough, Jeff Nelson opines “underperforming high-school students can relatively quickly transform themselves into highly successful college students – but that is almost impossible for them to make that transition without the help of a highly effective teacher” (p. 168). Pascarella and Terenzini (2005) report that academic resources that give students tutoring help and provide them opportunities to discuss their challenges produced statistically significant positive impacts on student persistence.

As educators we need to find out who our “clients” are, what works, what does not, and discover opportunities to fix it. “As the leader in business analytics software and services, SAS transforms your data into insights that give you a fresh perspective on your business. You can identify what’s working. Fix what isn’t. And discover new opportunities” (SAS.org). The SAS philosophy would indicate we need to know more about our students. With too many students not succeeding, teachers must continue to help stop the failing and dropping out trend of college students. Formulating a better understanding of who these learners are and what their struggles are may help determine possible predictors for their success. There is no prototypical student therefore there should not be just one prototypical remedial mathematics or college-level mathematics course. The varied student characteristics may require a variety of resources and approaches in a classroom.

The literature reviewed does not address the entire purpose of this research study. Obtaining demographic, cognitive, and non-cognitive characteristics of first-time freshmen students in mathematics courses, and describing correlations between these traits, can add to the existing research. Specifically, attaining answers to all research questions may help educational stakeholders provide opportunities that enable students to more effectively plan their work, family and academic life together, change their mindset, develop or increase metacognition and grit, so all students, notably those requiring remediation, have the opportunity to graduate and improve their career prospects. To help our students compete in the workplace, and have success in the lives, we must first understand who they are.

The next chapters, 3-5, are the research methodology, results, and discussion sections of the study. The methodology chapter includes the research design, instrumentation, participant, setting, and an outline of the data analyses. Chapter 4 discusses the results of the data analyses, while Chapter 5 includes the summary of the findings and implications for future research.

CHAPTER III

METHODOLOGY

This study used a quantitative research design to investigate three groups of first-time freshmen students enrolled in mathematics courses at a Midwest regional university. Grouping was based on the students need for mathematics remediation: no remediation required, partial remediation, and full remediation. A survey-design study was utilized to first gather participant demographic and non-cognitive characteristics. Survey research designs often use questionnaires or interviews to help identify participant beliefs, characteristics, and attitudes (Creswell, 2008). Additionally, precollege background information was gathered from university records, to help unveil the high school cognitive abilities of this population of first-time freshmen. Cross-sectional survey-designs also give researchers the opportunity to compare two or more educational groups, through statistical analysis of the data (Creswell, 2008). The second objective of this study was to compare the cognitive, demographic, and non-cognitive characteristics between the three groups. Lastly, this study aimed to determine which characteristic(s) predicted academic achievement (course grades) and retention the following semester. Chapter three outlines the research design, describes the setting, participants, instrumentation, data collection, and data analysis procedures.

The Research Questions

The following four research questions guided this study:

1. What are the characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of college freshmen enrolled in their first college mathematics course at a Midwest regional university?
2. Are there significant differences in demographic, cognitive, and non-cognitive traits (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) between groups (Full remediation, part remediation and no remediation) of college freshmen based on mathematics course enrollment?
3. Which characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of college freshmen enrolled in their first college mathematics courses at a Midwest regional university, are predictors of academic achievement as measured by final letter grades?
4. Which characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of freshmen students enrolled in a mathematics course requiring remediation at a Midwest regional university, are predictors of retention?

Research Design

This study utilized a cross-sectional survey-design approach with a sample that was both convenient and purposive. Survey-design research uses instruments and questionnaires to gather information from the participants in the study. “Surveys permit the researcher to summarize the characteristics of different groups or to measure their attitudes and opinions toward an issue” (Ary, et al., 2006, p. 31). To help develop a baseline understanding of freshmen mathematics students, survey instruments were used to gather student demographic information, their self-perceptions of brain malleability, perseverance, and self-regulatory processes. For this study, the instruments were used to both summarize and compare demographic, cognitive, and non-cognitive traits of freshmen mathematics students at a Midwest regional university.

Using inferential statistics, the study explored relationships or co-occurrences between these characteristics, which is symbolic of an explanatory correlational research design. Correlational studies measure the extent by which two or more variables are associated (Creswell, 2008). Additionally, correlational research may be of a prediction-design, whereby researchers look to determine whether two or more variables predict an outcome (Creswell, 2008). For this study, the researcher attempted to identify participant characteristics that predict academic achievement, as well as predict retention for students requiring mathematics remediation.

Research Setting

This study examined the demographic, cognitive, and non-cognitive characteristics of first-time freshmen students enrolled in a mathematics course at a

Midwest regional university. This public university is part of a statewide 6-school regional university system. This school offers 54 undergraduate majors/programs and 26 graduate programs. Approximately 7,000 undergraduate and nearly 1,200 graduate students were enrolled at the institution at the time of this study. Sixty-one percent of all students are female. This regional university mostly attracts in-state students (i.e., almost 92% of the enrollees are residents of the state in which the university resides). This large percentage of in-state students might help explain why only 18% of undergraduates live in university housing. Generally, class sizes at the school are less than 50 students per course (97%) but do range from single digit class sizes to over 70 per class. Courses at this institution are taught in a traditional fact-to-face lecture format, a blended format (part face-to-face, and part online), or strictly online. Full-time remediation courses are not offered as a completely online course. Mathematics courses are capped at 50 students per class. Students enrolled in a mathematics course requiring full remediation, along with partial remediation, and College Algebra often have the larger class enrollment numbers. The upper college-level mathematics courses, like Calculus and Introduction to Proof have under twenty students per class typically.

First-time freshmen enrolled at this Midwest regional university are eligible to be placed into a college-level mathematics course if their Mathematics ACT sub-score is greater than 18. Freshmen scoring lower than 19 must take the university mathematics placement test. The range for the Mathematics placement test is 20 to 120. Students scoring 75 or higher, may enroll in college-level mathematics. Students scoring below 19 on their ACT and below 44 on the placement test are designated to the lowest level course offered, which is Elementary Algebra. This is a course for students with little or

no previous algebra background, or need a review of basic algebra concepts. Included topics are signed numbers, fractions, percentages, exponents, order of operations, factoring, algebraic fractions, linear equations and inequalities, and word problems. Since these students do not meet university admission requirements, they require full remediation, thus no college credit is earned for this course. This remedial course is designed to prepare students for Intermediate Algebra.

Intermediate Algebra has traditionally been the second course in the remedial sequence at this Midwest regional university. First-time freshmen scoring below 19 on their ACT and scoring between 45 and 74 on the placement test were traditionally placed into Intermediate Algebra class. This is also a full remediation course for students that need to review their algebra in order to satisfy a high school deficiency. Included in the course is a brief review of topics from Elementary Algebra, along with radicals, rational expressions, factoring, linear equations and inequalities, absolute value, complex numbers, and quadratic equations. High school deficiency in mathematics may be satisfied by the successful completion of this course. No college credit is earned for this course.

In the Spring 2016 semester, this Midwest regional university began offering a Co-Requisite College Algebra course for students who, based on ACT and placement test scores, placed into Intermediate Algebra. This co-requisite course included a two-hour per week remediation component along with traditional College Algebra content. This 5-hour course afforded students who met Intermediate Algebra requirements, an opportunity to be remediated and receive College Algebra credit when passing the college-level course. During this study, Co-Requisite students met Monday, Wednesday,

and Friday to receive College Algebra content, while Tuesday and Thursday were designated as recitation time. During this time students worked on homework individually or in groups, received individual or group tutoring from the instructor, and sometimes received extra lecturing from the instructor. The aim of the two-hour remediation sessions were to provide the remedial students an opportunity to keep pace with and be as successful as the college-ready College Algebra students.

Population and Sample

Both purposive and convenience sampling techniques were used to amass participants for this study. In purposive sampling, researchers have a purpose in mind for a population that meet a certain profile. One purpose of this study was to understand key traits of first-time freshmen students enrolled in their first mathematics course. As for convenience sampling, Creswell (2008) stated researchers select “participants because they are willing and available to be studied” (p.155). Participants for this study came from a population of first-time freshmen students, who were 18 years or older, enrolled in a mathematics course at a Midwest regional university, and gave consent to this study.

At the beginning of the Fall 2016 semester, the first-time freshmen student population at the Midwest regional university totaled 877. Of that total, 660 first-time freshmen students enrolled in a mathematics course. By the final two weeks of the semester, there were 503 students still enrolled in a mathematics course. This group of first-time freshmen students were enrolled in either a college-level mathematics course or in a course requiring full or partial mathematics remediation, thus representing the population for this study.

Participants meeting minimum university ACT requirements, not needing mathematics remediation, enrolled in one of the following college-level mathematics courses: College Algebra, Applied Math, Statistics, Trigonometry, Calculus I, Discrete Mathematics, or Introduction to Proof. There were 285 first-time freshmen students (56.66% of 503), enrolled in one of these college-level mathematics courses at the Midwest regional university at the end of the Fall 2016 semester. The first-time freshmen enrolled in college-level courses were as follows: 301 in College Algebra, 2 in Applied Math, 6 in Trigonometry, 9 in Calculus I, 2 in Discrete Math, 19 in Statistical Methods, and 1 in Introduction to Proof.

There were 218 (43.3% of 503) first-time freshmen students enrolled in a mathematics course requiring remediation at the end of the Fall 2016 semester. This percentage mirrors the National Postsecondary Student Aid Study of 2003-04 (NPSAS:04), which found 43 percent of first- and second-year students enrolled in public two-year colleges took at least one remedial course during that year (Horn & Nevill, 2006). The majority of the students requiring mathematics remediation were enrolled in Elementary Algebra; 99 of the 218 (45.4%). This means nearly 20% (99 of 503) of all incoming freshmen students enrolling in a mathematics course at the Midwest regional university were in the lowest-leveled mathematics course offered at the institution. Intermediate Algebra and Co-Requisite Algebra courses had 55 and 64 students enrolled, respectively, near the end of the semester. Percentage-wise, 25.2% of remedial students were in Intermediate Algebra, while 29.4% were in a Co-Requisite Algebra course near the end of the semester.

All mathematics remediation courses (Elementary Algebra, Intermediate Algebra, and Co-requisite College Algebra) were offered in a traditional face-to-face classroom setting. Students enrolled in the required mathematics course that best fit their respective schedules (i.e., they randomly chose a time of day that best met their own needs). There were three sections of each level of remediation offered at the time of the study. The course learning objectives within each level of remediation were consistent between each section, regardless of times met each week. All students requiring mathematics remediation were expected to take the post-placement test in the computer lab at the end of the semester.

Demographically for this population of first-time freshmen, 42.5% were male ($n = 214$) and 57.5% were female ($n = 289$). According to university records, 86.5% were either 18 or 19 years of age ($n = 435$), 10.5% were between 20-24 years of age ($n = 53$), and 3% were over 25 years of age ($n = 15$). As for university ethnicity reporting categories, 40.4% were White ($n = 203$), 25.6% indicated two or more ethnicities ($n = 129$), 19.9% were American Indian ($n = 100$), 7% were Hispanic/Latino ($n = 35$), 3.6% were African American ($n = 18$), 2.2% were Non-Resident Alien ($n = 11$), 1.2% were Asian ($n = 6$), and 0.2% were unknown ($n = 1$).

Instrumentation

To collect both quantitative and categorical data for this study, the sources included an online survey and archival university records. The online survey consisted of a demographic section, and included three valid and reliable instruments. These quantitative instruments were the Grit Scale, Implicit theory of Intelligence Scale, and the

Metacognitive Awareness Inventory. Additionally, high school data (High School GPA, ACT Composite and Mathematics sub-scores), placement test scores and final mathematics course grades were collected from university records.

Demographic Survey

The demographic survey (See Appendix A) contains 22-items aimed to provide a holistic description of participants. Characteristics such as age, gender, ethnicity, marital status, number of children, job status, and parents'/guardians' educational levels were collected. The aim of this data collection was to help create an expansive demographic profile of each participant in this study.

Short Grit Scale (Grit-S)

The original 12-item Grit Scale (Grit-O) was developed to measure student capacity to sustain both effort and interest towards achieving a goal, in the face of adversity (Duckworth, et al., 2007). As a result of the Grit-O scale showing minimal evidence of predictive validity, Duckworth and Quinn (2009) conducted a series of studies on a shorter version, Grit-S, to investigate its validity and reliability. Their study indicated that scores on the Grit-S scale predicted military cadet retention, educational attainment amongst a sample of adults, and duration in a national spelling bee contest. The Grit-S scale has also been well-documented including reliability, a Cronbach alpha of 0.87, for example, was reported in a study on the grit of African American college students at a predominately white college (Strayhorn, 2013). The subsequent 8-item Likert-scaled instrument also addressed persistence in ones' interest over time and their ability to maintain effort through all setbacks. Sample items include: "I have overcome

setbacks,” or “I finish whatever I begin.” Each item contains a 5-point Likert-type response (*Very much like me, Mostly like me, Somewhat like me, Not much like me or Not me at all*). The score was determined by finding the sum of the Likert-scale responses and dividing this sum by eight (Duckworth & Quinn, 2009). The maximum score on this scale is five (extremely gritty) and the minimum score on this scale is one (Not gritty at all) (Duckworth & Quinn, 2009).

Implicit Theory of Intelligence Scale

According to Dweck & Leggett (1998), there are two implicit theories of one’s own intelligence: an entity theory, whereby the individual has a mindset that intelligence is fixed, and an incremental theory, one whereby the individual has a mindset that intelligence can grow. The Implicit Theory of Intelligence scale, used to determine whether a student had a fixed or a growth mindset, was developed by Dweck and colleagues in 1995, and consists of six Likert-scaled items. Children ranked their agreement to each of the item statements on a scale from 1 – 6: 1 (strongly agree), 2 (agree), 3 (mostly agree), 4 (mostly disagree), 5 (disagree), and 6 (strongly disagree). Half of the statements were written as incremental theory (growth mindset) statements, while the other half were written as entity theory (fixed mindset) statements. The three growth mindset statements were reverse-scored, so that strongly disagreeing with a fixed mindset statement indicated a strong agreement with a growth mindset. The total score indicated a growth, fixed, or neutral mindset. Students with average scores of 3 or lower were classified with a fixed mindset, while students averaging 4 or higher were deemed as having a growth mindset. Average scores falling between 3 and 4 (not inclusive)

indicated students did not have a distinct theory of intelligence (Dweck, Chiu & Hong, 1995).

Metacognitive Awareness Inventory

The Metacognitive Awareness Inventory (MAI) was developed by Schraw and Dennison (1994). The MAI is designed to measure metacognitive knowledge and metacognitive regulation. Metacognitive knowledge, the knowledge of one's own cognition, refers to what one knows about themselves, their own cognition, strategies, and conditions under which strategies are most useful. Metacognitive regulation, the regulation of one's own cognition, corresponds to the plan, goal setting, monitoring and evaluation strategies required for learning. This 52-item inventory asked students about strategies they use when approaching their coursework (Schraw & Dennison, 1994). Each item on the instrument is a statement about one's knowledge of how they learn or of the actions one must take to regulate their learning. MAI statements related to knowledge of cognition include: "I understand my intellectual strengths and weaknesses" and "I have control over how well I learn," and the following MAI metacognitive regulation statements: "I pace myself while learning in order to have enough time" and "I set specific goals before I begin a task" (Schraw and Dennison, 1994, p. 473). All statements are worded in a positive direction, with 17 related to knowledge of cognition, while 35 are regulation of cognition statements. Participants respond to each item using a Likert-type scale ranging from (5-*Very true of me*, to 3-*neutral* to 1-*Not at all true of me*). If the statement does not reflect one of these three responses, participants were directed to circle 2 or 4 revealing a "more or less like me" indication. A knowledge of cognition, regulation of cognition and a total metacognitive awareness score were each determined

by adding up the points. Higher scores indicate more knowledge of cognition and greater metacognitive regulation, and in combination the more metacognitive awareness one has. The MAI instrument was found to be both valid and reliable with an overall Cronbach alpha of 0.95, with similar sub-scales Cronbach alpha's of 0.91 for both knowledge of cognition and regulation of cognition (Schraw & Dennison, 1994). In their foundational work, the authors determined the two factors accounted for 65% of the sample variance. The authors suggest their results indicated that the MAI reliably measures knowledge of cognition and regulation of cognition based on the two-factor solution (Schraw & Dennison, 1994).

Course Grades

Final letter grades in a course were based on class average percent scores. Class average percent scores may not have been calculated uniformly at the Midwest regional university, however final letter grades are still consistently used as a measure of academic achievement. Aspects of final class averages may have included, but were not be limited to chapter test scores, homework or quizzes, attendance or tutor points, and final exam scores. For students requiring full mathematics remediation (Elementary or Intermediate Algebra) at the university in this study, letter grades of A, B, and C are considered passing grades, and passing students were then eligible to enroll in the next course in the sequence. A grade of "D" is not allowed to be given; thus, a student with a percentage in this range would have received an F and would likely have to repeat the course.

ACCUPLACER Computer Placement Test

The ACCUPLACER Computer Placement Test (CPT) is an Elementary Algebra-level test administered at the site of this study. The university testing center administers the CPT, and enters the raw scores on a secure campus database.

The CPT is used for two reasons at the institution. First, the CPT is used for the placement of freshmen into an appropriate mathematics course. Students who scored below 19 on the mathematics portion of the ACT are directed to take the CPT. If a student scores below 44 on the CPT they are enrolled in an Elementary Algebra class. If a student scores between 45 and 74 they are directed to enroll in Intermediate Algebra (second remedial mathematics course in the sequence), or enroll in a co-requisite College Algebra course. Students scoring 75 or above on the CPT are allowed to enroll in college-level coursework.

The second manner for which the CPT is administered is as the final exam for the co-requisite college algebra and for both remedial mathematics courses. This has provided the Mathematics Department a means to assess student improvement in algebra by viewing pre- and post-test scores. It also affords students the opportunity to place into the next 'higher' course, regardless of the course grade received. This means students who receive an 'F' letter grade (i.e., do not satisfactorily meet the semester-long academic requirements) may score high enough on the CPT to place into the next course in the sequence.

The CPT itself, is deemed an adaptive test since subsequent test questions are based on previous answers given; therefore, each question must be answered before the next one can be assigned. More challenging questions are presented as the demonstrated

skill level increases. The 12-questions are multiple choice and students are not timed and are not allowed to use calculators or cell phones. CPT elementary algebra questions may include the following mathematics topics: order of operations, scientific notation, substitution, linear equations in one variable, formulas, word problems, inequalities, exponents and polynomials, factoring, quadratic equations, rational expressions, graphing, system of equations, and radicals.

Data Collection

Data collection for this study was conducted in three phases. Table 3.1 provides an overview of these phases. Before data collection though, the researcher gained university International Review Board (IRB) approval. The researcher then solicited freshmen mathematics student participation in the study. All potential participants enrolled in college-level mathematics and remediation courses at the institution, were sent a recruitment email. The email included the purpose of the study and a link to a Qualtrics survey. The first page of the Qualtrics survey was a consent form, which included a statement to the participants indicating by completing the survey provides their informed consent. A notification also stated that their participation is voluntary and they could have withdrawn from the study at any point in time. Students, 18 years or older, giving consent were then asked to complete the survey (demographics, mindset, grit, and metacognitive awareness), which included selected response and Likert-type scale questions.

Table 3.1

<i>Phases of Data Collection</i>		
Phase 1 (Nov. 2016)	Phase 2 (Dec. 2016)	Phase 3 (Jan. 2017)
Demographic Survey	Post-Placement	Retention Rates
Grit Scale	Final Grades	
Implicit Theory Scale		
MAI		
High School and ACT data		
Pre-Placement		

Once all data were collected for each student, all names were removed, and a code was used to protect the identity of each participant. Only the researcher had access to the codes and these were stored in a secured and locked cabinet, separate from all data. A two-week window in late November of 2016 was allocated for Phase 1 of data collection, in which to paint a picture of the incoming freshmen students enrolled in mathematics courses at the university.

From University Records, initial placement test scores were collected for students enrolled in a mathematics remediation course, which may also be used as baseline academic achievement indicator for this group of students. High school GPA, overall composite ACT and Mathematics ACT sub-scores were also collected as part of the second phase (see Table 3.1). Phase 2 data collection occurred at the end of the semester, when final letter grades and post-placement test scores were available to be collected. The researcher had access to post-placement test scores, for all students enrolled in a

course requiring mathematics remediation, on the university assessment data bank. This collection took place on December 9, 2016 (the last day of Final Exams). The researcher gathered final letter grades for all participants, from the Mathematics Department Chair at the Midwest regional university. Final letter grades were due by December 13, 2016, thus were collected the following day. Phase one and two data collection helped in addressing the first three research questions.

For the last phase, retention rates of students enrolled in any mathematics course requiring remediation, were collected after the add/drop date at the beginning of the ensuing semester, Spring 2017. The goal of this last phase was to gather and assess the retention rates (re-enrollment at the university) for this group of participants.

Data Analysis

The researcher aimed to describe the characteristics of freshmen mathematics students at a Midwest regional university, determine if there were characteristic differences based on enrolled mathematics course, determine predictive nature of characteristics, and calculate retention rates of the students requiring remediation. Table 3.2 describes the analysis that was used to answer each research question.

Table 3.2

Planned Analyses for Research Questions

Research Question	Planned Analysis
1. What are the characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of college freshmen enrolled in their first college mathematics course at a Midwest regional university?	Descriptive Statistics; specifically the mean, range and standard deviation, will be calculated and reported during the data analysis for the first question
2. Are there significant differences in demographic, cognitive, and non-cognitive traits (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) between groups (Full remediation, part remediation, and no remediation) of college freshmen based on mathematics course enrollment?	ANOVA and Chi-Square Tests of Independence
3. Which characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of college freshmen enrolled in their first college mathematics courses at a Midwest regional university, are predictors of academic achievement as measured by final letter grades?	Hierarchical regression analysis
4. Which characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of freshmen students enrolled in a mathematics course requiring remediation at a Midwest regional university, are predictors of retention?	Logistical regression analysis

Ethical Considerations

The researcher considered ethical issues at all times. Personal information gathered for this study remained confidential and was coded to ensure participant

anonymity. The electronic questionnaires and surveys are stored on a password-protected computer. The computer used by the researcher is user and password protected and resides in a locked office. Access is therefore limited to the researcher only. Any publication material generated by the researcher will also not expose the identity of any persons included in the study. Fabrication or falsification of any data or results will not take place. Again, participants wanting to leave the study, did so without implications, at any time. Students who did participate in the study (i.e., give consent) were entered into a prize drawing. Three prizes were given to three randomly selected participants. Giving an incentive helped encourage participation in the study, and helped compensate for time required to participate.

Summary

The purpose of the survey-design study was to describe the freshmen mathematics students at a Midwest regional university by gathering educational background facts, demographic data, non-cognitive and metacognitive characteristics. Differences in mindset, metacognitive awareness, and levels of grit between subgroups, were also calculated. Additionally, correlational analysis was conducted to determine relationships between student characteristics and academic achievement, as well as their characteristics and retention.

This design, participants, procedures, instruments, research questions, and analysis are summarized in this chapter. The results of the data analysis is presented in Chapter IV and a discussion of these results will follow in Chapter V.

CHAPTER IV

RESULTS

This quantitative study explored the characteristics of first-time freshmen enrolled in mathematics courses at a Midwest regional university, and investigated which of these characteristics might predict academic achievement and retention the following semester. The research questions guiding the study are:

1. What are the characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of college freshmen enrolled in their first college mathematics course at a Midwest regional university?
2. Are there significant differences in demographic, cognitive, and non-cognitive traits (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) between groups (Full remediation, part remediation and no remediation) of college freshmen based on mathematics course enrollment?
3. Which characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of college freshmen enrolled their first college mathematics course, are predictors of academic achievement as measured by final letter grades.

4. Which characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of freshmen students enrolled in a mathematics course requiring remediation at a Midwest regional university, are predictors of retention?

In the following sections, findings of this study are presented as they relate to these research questions. Data will be presented across the various subgroups of first-time freshmen enrolled at a Midwest regional university, according to their level of remediation (no, partial, and full).

Characteristics of First-time Freshmen Enrolled in a Mathematics Course

In order to provide support for first-time freshmen students enrolling in mathematics courses it is important to gain an understanding of who these students are. Thus, a variety of demographic, cognitive, and non-cognitive data were collected. To determine these baseline characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of first-time freshmen, I analyzed online survey and archival data. Descriptive statistics including frequency distribution, measures of central tendency and dispersion were calculated.

Demographic Characteristics

Demographic information painted a picture of who the participants are in the study. For this study, the sample participants self-reported demographic information via an online survey. Since the sample for this research were first-time freshmen college students at a 4-year university it was not surprising to find that 94% of this group were

single and 93% had no children of their own. Demographic characteristics of participants in the online survey are displayed in a frequency distribution (see Table 4.1).

Table 4.1

Demographic Characteristics as a Percent of the Sample – By Remediation Group

Characteristic	All (%) <i>n</i> = 159	Full (%) <i>n</i> = 50	Part (%) <i>n</i> = 26	No (%) <i>n</i> = 83
Gender				
Male	25.8	28.0	25.0	24.7
Female	74.2	72.0	75.0	75.3
Age (years)				
18-19	88.1	76.0	92.6	94
20-24	8.8	14.0	7.4	6.0
25+	3.1	10.0	0.0	0.0
Ethnicity				
White	47.2	44.0	34.6	53.0
African American	3.8	2.0	7.7	3.6
Native American	24.5	30.0	42.3	15.7
Asian	2.5	0.0	0.0	4.8
Hispanic	3.8	2.0	3.8	4.8
Two or more	17.6	22.0	11.5	18.1
Employment Status (per wk.)				
Not Employed	51.6	56.0	53.8	48.2
Employed (>20hrs.)	16.4	20.0	15.4	18.1
Employed (≤ 20hrs.)	23.3	18.0	19.2	30.1
Father's Education Level				
Bachelor's Degree (+)	20.1	6.0	34.6	24.1
Assoc./Voc./Tech. Deg.	14.5	12.0	7.7	18.1
Did not finish college	9.4	10.0	3.8	10.8
High School/GED	40.9	52.0	42.3	33.7
Did not finish H.S./GED	5.7	4.0	3.8	7.2
Do Not Know	9.4	16.0	7.7	6.0
Mother's Education Level				
Bachelor's Degree (+)	33.3	28.0	19.2	41.0
Assoc./Voc./Tech. Deg.	12.6	16.0	23.1	7.2
Did not finish college	13.8	12.0	11.5	15.7
High School/GED	30.2	28.0	46.2	26.5
Did not finish H.S./GED	5.0	8.0	0.0	4.8
Do Not Know	5.0	8.0	0.0	4.8

First, examining the gender, age, and ethnicity of participants (refer to Table 4.1) it was noted that higher percentages of female participants completed the survey, than were males. The majority of all participants in the study were 18 or 19 years of age (88.1%). The only group containing student participants 25 years of age or older, were the Full-time remediation mathematics classes. Over seventy percent of the sample self-reported as being either White/Caucasian (47.2%) or Native American (24.5%). When including multi-ethnic self-reporting numbers, over 86% of the participants in each group were either white, native or multi-racial. More than half (53%) of the college-level non-remediated mathematics participants were White/Caucasian, and there were higher percentages of Whites/Caucasians enrolled in full-time remediation (44%) classes as well. In comparison to the overall sample, Native American student participants had a higher percent in the part-time remediated mathematics classes (42.3%), and a lower representation (15.7%) in college-level courses (i.e., no remediation). While 2.5% of all participants were Asian, there were no Asian participants in a mathematics course that required any level of remediation. In all, there were identical percentages of Hispanic and African American student participants (3.8%), and very few of these students required full remediation.

In addition to the typical demographic information, it is important to examine other influences from outside of the classroom that may contribute to student success inside the classroom. The hours worked each week during the semester, and the educational backgrounds of each parent, or guardian, were collected for each participant. Approximately half of the student participants in each group reported they did not work during the semester. Slightly higher percentages of full-time remediation mathematics

students (20%) reported working more than 20 hours each week, compared to the partial remediation (15.4%) and no-remediation groups (18.1%). Nearly twice as many students not requiring remediation reported they worked less than 20 hours per week versus more than 20. A slightly lower percent of student workers requiring partial remediation reported more than 20 hours per week versus less than 20.

Another demographic factor, exterior to the classroom, in this study was the parental educational level of the participants. Student mathematics enrollments may depend on their parents/guardians education levels. For students enrolled in a full-time remediated mathematics class, 28% reported their father had at least attended college, compared to 46.1% for partial remediation students, and 53% for students enrolled in a college-level course. Conversely, 56% of the full time remediation mathematics students reported their father had at most a high school degree or a GED, compared to 46.1% of the part-time and 40.9% of the student participants not needing remediation. This implies a higher percentage of fulltime remediation students have fathers who have no college experience (i.e., did not attend college). As for Mother's education level, 56% of fulltime remediated mathematics students reported their mother had at least attended college, compared to 53.8% for part-time remediated students and 63.9% of the college-level students not requiring remediation. Lower percentages of college-level (No remediation = 31.3%) participants reported their mother achieved at most, a high school diploma or GED at most, compared to the other two groups. This may indicate that the more education the mother has, the less one is likely to enroll in a remediated mathematics course.

Cognitive Characteristics

To gain an understanding of academic levels of first-time freshmen, university records were used to collect participant's High school GPA, ACT Composite, ACT Mathematics and pre-placement test scores. Table 4.2 and 4.3 display the precollege cognitive descriptive statistics for all participants and across the three subgroups of the participants.

Table 4.2

Descriptive Statistics Cognitive Variables – By Remediation Group

Cognitive Variables	<i>n</i>	<i>M (SD)</i>	95% Confidence Interval for the Mean	
			LL	UL
GPA - All	153	3.43 (0.46)	3.36	3.50
Full	46	3.20 (0.38)	3.09	3.31
Part	26	3.29 (0.48)	3.10	3.49
No	81	3.61 (0.39)	3.52	3.70
ACT Comp. - All	152	20.72 (3.63)	20.13	21.30
Full	44	18.27 (2.81)	17.42	19.13
Part	26	18.58 (1.94)	17.79	19.36
No	82	22.71 (3.25)	21.99	23.42
ACT Math - All	152	19.48 (3.64)	18.90	20.06
Full	44	16.25 (1.14)	15.90	16.60
Part	26	16.96 (0.92)	16.59	17.33
No	82	22.01(3.09)	21.33	22.69

Examination of means and standard deviations, it appears the students who did not need remediation had the highest mean high school GPA, Composite ACT, and ACT Mathematics sub-scores. Conversely, students enrolled in a full-time non-credit bearing remediated mathematics course had the lowest mean high school GPA and ACT scores, though these did not seem much lower than the part-time remediated students.

For some students, another measure of their academic level as they entered college, was the computer placement test (CPT). Students not meeting university entrance requirements (19 or higher ACT Mathematics sub-score) were required to take a placement test prior to enrolling for their first semester in mathematics. Participants who scored below 19 on the ACT and below 75 on the university CPT were placed into one of three mathematics remediation courses based on their CPT score. The minimum possible placement test score is 20 and the maximum 120. Students scoring below 16 on the mathematics section of the ACT and below 44 on the CPT, were placed into Elementary Algebra, a non-credit full-time remediation mathematics course, which is the lowest level offered at the university. Students scoring 17 or 18 on the mathematics section of the ACT or between 45 and 74 on the CPT, had the option of enrolling in a 3-hour fully remediated Intermediate Algebra course, which had been the traditional subsequent course to Elementary Algebra, or a 5-hour Co-requisite College Algebra course which includes 2 hours of part-time remediation. Table 4.3 displays the pre-placement test descriptive statistics for the two levels of full remediation and the part-time co-requisite college algebra group.

Table 4.3

Descriptive Statistics for Pre-CPT Scores – By Remediation Group

Level of Remediation	<i>n</i>	<i>M (SD)</i>	Min.	Max.	95% Confidence Interval for the Mean	
					LL	UL
Pre-CPT- All	75	42.37(12.30)	21	70	39.54	45.20
EA	33	33.12 (8.57)	21	63	30.08	36.16
IA	17	47.94 (11.73)	21	66	41.91	53.97
CR	25	50.80 (7.95)	34	70	47.52	54.08

Note. EA – Elementary Algebra. IA- Intermediate Algebra. CR- Co-requisite College Algebra.

As expected, students mean CPT scores were lower for the students in Elementary Algebra ($M = 33.12$) because university placement policies enroll students in remediated mathematics courses based on the placement test score. Therefore students scoring below 44 were placed into Elementary Algebra. Student mean CPT scores for the co-requisite college algebra students ($M = 50.80$) were higher than the Intermediate Algebra students ($M = 47.94$), and the range of scores for the co-requisite students (34-70) was narrower than the Intermediate Algebra students (21-66).

Non-Cognitive Characteristics

“Two students with equal academic abilities can respond in remarkably different ways to frustration, with one relishing the opportunity to learn and the other becoming demoralized and giving up” (Dweck, et al., 2011, p. 5). This infers cognitive abilities are not the sole reason for student success, i.e., non-cognitive characteristics may play a part in the academic achievement of students as well. Thus, participant data were collected on

the mindset, level of grit, and the meta-cognitive awareness of the three groups of students.

Mindset. Participant mindsets were measured using Dweck's six-item Implicit Theory of Intelligence scale (1999). Mean scores were calculated based on student responses to three fixed mindset and three growth mindset statements. For the growth mindset statements, a Strongly Agree selection was scored a 6, followed in descending value to Strongly Disagree which was scored a 1. The fixed mindset statements were reverse coded, i.e., Strongly Disagree (scored 6) down to Strongly Agreed (scored 1). The sum of participant responses to six statements were divided by six to determine their mean score (ranging from 1 to 6), with a higher score indicating a growth mindset. For the sample of students in this study, the internal reliability of the Implicit Theory of Intelligence Scale was .87, which indicates a high level of internal consistency. Table 4.4 displays the mean, standard deviation, and confidence intervals for the mindset of each group, as well as all participants.

Table 4.4

Descriptive Statistics for Mindset – By Remediation Group

Group	<i>n</i>	<i>M (SD)</i>	95% Confidence Interval for the Mean	
			LL	UL
Full	50	4.41 (0.97)	4.13	4.68
Part	26	4.46 (1.11)	4.01	4.91
No	83	4.37 (0.87)	4.18	4.56
All	159	4.40 (0.94)	4.25	4.54

The mean mindset scores did not seem to vary much between groups. The means ranged from 4.37 for students not requiring remediation, to 4.46 for students enrolled in mathematics remediation part-time. The full-time remediation mathematics group had a mean of 4.41, which falls between the other two group means. This entire sample of students are classified as having a growth mindset since their mean scores were in the range of 4.0-6.0. Scores below 3.0 are deemed fixed mindset theorists.

Grit. The perseverance and passion towards achieving a long-term goal, is a measure of one's grit. Perseverance is the dedication, stamina, effort through challenges and failures, while consistent interest and remaining loyal to the goal, is the passion part of grit (Duckworth, et al., 2007).

To determine levels of grit, participants responded to items on the Grit Scale developed by Duckworth and Quinn (2009). Mean grit scores were calculated based on student responses to statements regarding perseverance and passion towards mathematics. A sample statement is "In mathematics, I am a hard worker." Statements indicating grit

were scored as follows: 5 = Very Much Like Me, 4 = Mostly Like Me, 3 = Somewhat Like Me, 2 = Not Much Like Me, and 1 = Not Like Me At All. Statements not indicating grit (no or low perseverance and passion) were reverse coded, i.e., Not Like Me At All (scored 5) down to Very Much Like Me (scored 1). Student means could range from 1 to 5. High scores indicate more grit. For the sample of students in this study, the internal reliability of the Grit Scale was .80, which indicates a high level of internal consistency. Table 4.5 displays the mean, standard deviation, and confidence intervals for the level of grit of each group, as well as all participants.

Table 4.5

Descriptive Statistics for Grit – By Remediation Group

Group	<i>n</i>	<i>M (SD)</i>	95% Confidence Interval for the Mean	
			LL	UL
Full	50	3.24 (0.65)	3.06	3.43
Part	26	3.25 (0.68)	2.98	3.53
No	83	3.55 (0.72)	3.39	3.71
All	159	3.40 (0.70)	3.29	3.51

Based on observations of the means and standard deviations in Table 4.5, it appears there is a trend in Grit levels based on grouping. The students requiring no remediation had the highest mean grit score, which implies they have more grit than the other two groups requiring remediation, which may be interpreted as they finish tasks, achieve goals, and maintain interest more than the less gritty student groups. The mean grit score for the part-time remediation group was higher than the mean grit score of the

full-time remediation mathematics group, however these mean scores seem to indicate similar levels of grit.

Metacognitive Awareness. “Metacognition is generally defined as the activity of monitoring and controlling one’s cognition” (Yound & Fry, 2008, p.1). The third non-cognitive characteristic in the study involved student awareness of their own learning. The Metacognitive Awareness Inventory (MAI) was designed to determine the level at which students know how they learn and regulate their own learning (Schraw & Dennison, 1994). Student responses to the 52-item MAI were recorded. An MAI Total is the sum of all 52-item responses, which has a range from 52 to 260, based on Very True of Me (score of 5) through Neutral (score of 3) down to Not At All True of Me (score of 1). Scores of 4 and 2 were to be thought of as Somewhat Like Me or Somewhat Not Like Me, respectively. Higher scores indicate a higher awareness of cognition. For the sample of students in this study, the internal reliability of the Metacognitive Awareness Inventory was .96, which indicates a high level of internal consistency.

Two sub-components of metacognition, knowledge of cognition and regulation of cognition were also determined. Seventeen of the 52 statements are related to Knowledge of Cognition (K of C), while the remaining 35 are related to Recognition of Cognition (R of C). Therefore the possible range for each of these subsets are 17-85, and 35-175 respectively. Higher scores on these sub-components also indicate greater metacognitive knowledge and greater regulation of knowledge. For the sample of students in this study, the internal reliability of the MAI sub-scales (K of C and R of C) were .91 and .94, respectively, which each indicate a high level of internal consistency.

Table 4.6 displays the mean, standard deviation, and confidence intervals for all students in the sample and for each group.

Table 4.6

Descriptive Statistics Metacognitive Awareness Components – By Remediation Group

	<i>n</i>	<i>M (SD)</i>	95% Confidence Interval for the Mean	
			LL	UL
MAI Sum-All	159	183.36 (31.07)	178.50	188.23
Full	50	174.72 (37.06)	164.19	185.25
Part	26	179.31 (32.39)	166.23	192.39
No	83	189.84 (25.03)	184.38	195.31
K of C - All	159	63.11 (10.37)	61.49	64.74
Full	50	59.58 (11.18)	56.40	62.76
Part	26	60.77 (11.63)	56.07	65.47
No	83	65.98 (8.59)	64.10	67.85
R of C - All	159	120.25 (22.14)	116.78	123.72
Full	50	115.14 (26.83)	107.52	122.76
Part	26	118.54 (21.89)	109.70	127.38
No	83	123.87 (18.39)	119.85	127.88

Note. MAI – Metacognitive Awareness Inventory, K of C - Knowledge of Cognition, and R of C - Regulation of Cognition.

Based on observations of the means and standard deviations in Table 4.6 there appears to be a trend in all MAI variables between the groups. The mean total metacognitive scores of the non-remediation students ($M = 189.84$) were higher than the means of the students requiring part-time remediation ($M = 179.31$), and these part-time

means were higher than full-time remediated mathematics student means ($M = 174.72$). Knowledge of cognition and regulation of cognition means followed that same trend. The higher means in all three categories, implies students in a college-level (no remediation) mathematics course are more aware of how they learn, and regulate their learning more, as compared to the other two groups which required mathematics remediation.

Differences of the Characteristics of the Groups of First-time Freshmen

After determining descriptive statistics for the variety of demographic, cognitive, and non-cognitive characteristics for each group of first-time freshmen mathematics participants, the next phase of the study was to determine if there were any statistically significant differences between the groups. Thus, for the variety of traits (i.e., demographic, cognitive and non-cognitive) of first-time freshmen, the researcher analyzed the data for potential significant differences.

Demographic Characteristics

“When dealing with nominal data, the most widely used tests of significance are the chi-square tests” (Ary, et al., 2006, p. 206). The chi-square test of independence was used to determine if two demographic (categorical) variables were associated, in other words, if the proportions remain the same for the categories. The demographic variables (gender, ethnicity, parental education, and job status) were analyzed for association or independence with a particular group (full, part or no mathematics remediation). For results of a chi-square test of independence to be valid, there must be two categorical variables, with two or more groups for each category, observations must be independent,

there must be a relatively large sample size, and frequencies should be at least 5 for the cells within each category. The gender data met all of these chi-square assumptions. Ethnicity, parental education levels, and job status did not meet the latter assumption that each cell had at least a frequency of 5. As a result, data within each of these three demographic categories were collapsed to meet this frequency requirement. Ethnicity was collapsed to two categories: *over-represented* (non-Hispanic White and Asian) and *under-represented* (African and Native American, Hispanic and Multi-racial) groups. For the parental education level, Bachelor's degree, Associates (Vo/Tech) degree and Did Not Finish College were collapsed to *some college*, and the others collapsed to *no college*. To reach a frequency of 5 for each cell in the Job Status category, the data were collapsed to *Work/Have a Job* and *No Job*.

Gender. The chi-square test of independence was performed to examine the relation between gender and the groups of mathematics students. The relation between these variables was not significant ($\chi^2(2) = .238, p = .888$). Another way to state this is to say that gender and remediation requirements are independent of each other, which suggests the proportion of male and female students in each mathematics group were similar. Nearly three-fourths of all participants in all groups are female (see Table 4.1).

Ethnicity. Ethnicity was originally divided into six categories: White, African American, Native American, Hispanic, Asian, and Multi-racial. Since some racial categories for this study had low (less than 5) or no representation within some of the mathematics groups, for the purposes of examining relations between ethnicity and mathematics group, ethnicity was collapsed to *over-represented* (White and Asian) and

under-represented groups (all others). The researcher chose to pair the two ethnicities in the over-represented group because of the academic subject in the study. In an ACT (2016) report on students meeting ACT college readiness mathematics benchmarks, it found 70% of Asian American and 50 % of White high school seniors were mathematically ready for college. The percent of students from other ethnicities who met the benchmark mathematics scores indicating college readiness were much lower, with a low of 13% African American to a high of 27% Hispanic, with Native American percentages (18%) falling in between the two. Also, as there has been an increase in enrollment in college for all ethnicities, increases by White and Asian students still make up higher percentages of 4-year institution United States enrollment numbers, compared to Hispanic, African American and Native American students (NCES, 2015). An additional reason for dividing ethnicity into these two categories, over-represented and under-represented, was the fact that higher percentages of first-time freshmen Asian (69%) and White (62%) students graduate college with a bachelor's degree within six years, compared to Hispanic (50%), African and Native American (39% each) students (NCES, 2017). In concordance with the under-representation label, African American and Hispanic students accounted for 12% of all bachelor's degrees earned in Oklahoma in 2012-2013 (SREB, 2015). These facts helped justify the aforementioned split into over- and under-representative groups.

The result of the chi-square test of independence indicated there were differences, between mathematics groups, in the proportionality of *under-* and *over-represented* students, though the differences were not quite significant ($\chi^2 (2) = 5.212, p = .074$). Table 4.7 shows there were higher percentages of White and Asian (57.8%) students in

the college-level non-remedial mathematics group, compared to under-represented students (42.2%). Conversely, for students taking any course that required mathematics remediation, there were higher proportions of under-represented students (Black, Native American, Hispanic, and Multi-racial) versus over-represented.

Table 4.7

Ethnicity Percentages by Remediation Group

	Over-represented	Under-represented	Total
	<i>n</i> (%)	<i>n</i> (%)	<i>n</i> (%)
Full Remediation	22 (44.0)	28 (56.0)	50 (100)
Part Remediation	9 (34.6)	17 (65.4)	26 (100)
No Remediation	48 (57.8)	35 (42.2)	83 (100)
Total	79 (49.7)	80 (50.3)	159 (100)

Note. Over-represented: White/Caucasian and Asian. Under-represented: African American, Native American, Hispanic, and Multiracial.

Parents' Educational Level. The education level of the parent was originally divided into six categories: bachelor's degree or higher, two-year (associates, vocational or technical) degree, did not finish college, high school diploma (or GED), did not graduate high school (or no GED), and do not know. Since the data for the educational level of the father and the educational level of the mother had some frequency counts that were less than five, the data were collapsed into two categories, *some college* and *no college*. Parents that at least attended college (earned any degree, or did not finish college) were collapsed into the *some college* category, while the other original three categories were collapsed to *no college*. Some participants indicated they did not know

the education level of their parent. This data were sorted as *no college* with the idea that the parent had no direct impact on the student's choice to attend college.

Thus, the relation between parent's educational levels and mathematics groups were individually subjected to the chi-square test of independence. The results revealed a significant difference ($\chi^2 (2) = 7.979, p = .019$) in father's educational level between groups (full remediation, part-remediation and no remediation) of mathematics students. Students in a full-time remediation mathematics course had a significantly higher percent (72%) of fathers having never attended college compared to the other two groups (see Table 4.8). Another way to state this is to say that enrollment in a full-time remediation mathematics course is strongly related to whether the father attended college or not.

Table 4.8

Father's Education Percentages by Remediation Group

	Some College <i>n</i> (%)	No College <i>n</i> (%)	Total <i>n</i> (%)
Full Remediation	14 (28.0)	36 (72.0)	50 (100)
Part Remediation	12 (46.2)	14 (53.8)	26 (100)
No Remediation	44 (53.0)	39 (47.0)	83 (100)
Total	70 (44.0)	89 (56.0)	159 (100)

There was no significant difference found between mathematics groups and the mother's educational level ($\chi^2 (2) = 1.251, p = .535$), however, each group had higher percentages of mothers having at least gone to college, than never attending (see Table 4.9). The students not in a remediation group had the highest percent of mothers

attending college (63.9%). If there were an association between mother's education and the mathematics remediation status, we would have expected these percentages to differ significantly between groups in some way.

Table 4.9

Mother's Education Percentages by Remediation Group

	Some College <i>n</i> (%)	No College <i>n</i> (%)	Total <i>n</i> (%)
Full Remediation	28 (56.0)	22 (44.0)	50 (100)
Part Remediation	14 (53.8)	12 (46.2)	26 (100)
No Remediation	53 (63.9)	30 (36.1)	83 (100)
Total	95 (59.7)	64 (40.3)	159 (100)

Job Status. The original survey asked students to report if they worked, yes or no, and if so was it more than or less than 20 hours each week. Again, there were frequency responses to these questions that totaled less than five. Therefore, the data were collapsed into either *having a job* (working any number of hours), or *no job*. This dichotomous data were tested for independence with mathematics group. The results of the chi-square test ($\chi^2 (2) = .826, p = .662$) indicated there was no relation between mathematics groups and job status. In other words, there was an equal proportion of students having a job, or not having a job, in each of the three mathematics groups.

Cognitive Characteristics

To gain an understanding of the differences in the academic levels of the three groups of first-time freshmen mathematics students, data representing the means for each

precollege cognitive trait (High school GPA, ACT Composite, ACT Mathematics and pre-placement test scores) were analyzed for differences.

To determine statistically significant differences between the groups of participants regarding cognitive variables, ANOVA tests were conducted. Tests for homogeneity of variance and normal distribution were conducted prior to each ANOVA test. When one or both of these two assumptions were not met, a description of the procedures taken are included in the relevant sections below. The third assumption, independence, was met since individual participants each randomly enrolled in various mathematics courses based on their personal schedules, and they individually completed the online survey since it was sent to their personal email addresses.

High School Grade Point Average. The distribution of High School Grade Point Average (GPA) scores met the assumption of homogeneity of variances (Levene's Test = .492), but did not meet the assumption of normality for the sample data. Due to the non-normal distribution, the Kruskal-Wallis nonparametric test was used to determine significant differences between group GPA's. The results of this test indicated a significant difference in mean GPA between groups ($\chi^2 (2) = 37.831, p < .001$). Thus, Tukey HSD post hoc analyses were conducted on all possible pairwise comparisons, to determine where the significance occurred.

As Table 4.10 indicates, the following groups were found to have statistically significant differences ($p < .05$): No remediation ($SD = .39$) compared to Part remediation ($SD = .48$) and No remediation ($SD = .39$) to Full remediation ($SD = .38$). In other words, students not requiring any remediation had significantly higher High School

GPA's than the two groups requiring some remediation. There were no significant differences found between the part-time and full-time remediation mathematics student GPA's.

Table 4.10

Tukey HSD - Multiple Comparisons of Differences in Group Mean High School GPA's

	Group 1: Full	Group 2: Part	Group 3: No
Full ($M = 3.20$)	-	-.095	-.411*
Part ($M = 3.29$)		-	-.316*
No ($M = 3.61$)			-

* $p < .05$.

ACT Scores. The ACT scores, Composite and Mathematics subscale, were tested for homogeneity of variances and normality. Both sets of scores did not meet the normality assumption. ACT Composite variances were homogeneous, however the ACT Mathematics scores did not meet the homogeneity of variance assumption. The Kruskal-Wallis nonparametric test was conducted again to determine significant differences in mean ACT scores between the groups. Though this test makes no normality assumption, it still assumes equal population variances. Lomax and Hahs-Vaughn (2012) however, claim “heterogeneity does have some effect on this test, but it is less than with the parametric ANOVA” (p. 22). The results of the Kruskal-Wallis nonparametric test indicated a significant difference in mean ACT Composite scores between groups ($\chi^2 (2) = 53.334, p < .001$), and significant differences in mean ACT Mathematics subscale scores between groups ($\chi^2 (2) = 94.037, p < .001$).

Since ACT scores did not meet the homogeneity of variance assumption, a Welch Test was also conducted. The results also indicated mean ACT Composite were significantly different between all groups ($F(2, 80.23) = 37.027, p < .001$) and mean ACT Mathematics subscale scores as well ($F(2, 67.91) = 110.637, p < .001$).

As a result of differences being found, Tukey HSD post hoc analyses were conducted on all possible pairwise comparisons of mean ACT Composite and mean ACT Mathematics scores, to determine where the significance occurs. Tables 4.11 displays the results of the multiple comparison analyses.

Table 4.11

Tukey HSD - Multiple Comparisons of Differences in Mean ACT Composite and Mathematics Subscale Score by Remediation Group

<i>ACT Composite</i>	Full	Part	No
Full ($M = 18.27$)	-	-.304	-4.435*
Part ($M = 18.58$)		-	-4.130*
No ($M = 22.71$)			-
<i>ACT Mathematics Subscale</i>			
Full ($M = 16.25$)	-	-.712	-5.762*
Part ($M = 16.96$)		-	-5.051*
No ($M = 22.01$)			-

* $p < .05$.

For ACT Composite, the following groups were found to be significantly different: No remediation ($SD = 3.25$) compared to Part remediation ($SD = 1.94$) and No remediation ($SD = 3.25$) to Full remediation ($SD = 2.06$). For ACT Math, the following groups were found to be significantly different ($p < .05$): No remediation ($SD = .309$) compared to Part remediation ($SD = .92$) and No remediation ($SD = .309$) to Full

remediation ($SD = 1.14$). These results suggest the mean ACT Composite and ACT Mathematics scores for those not requiring remediation were significantly higher than students enrolled in either a full or part-time remediation mathematics course. There were no significant differences found between the part-time and full-time remediated mathematics student mean ACT Composite or ACT Mathematics scores.

Pre-Computer Placement Test. The Pre-Computer Placement Test (Pre-CPT) data for the participants enrolled in a course requiring remediation, met the assumption of homogeneity of variances according to Levene's test ($F(2,72) = .720, p = .490$). A review of the Shapiro-Wilk test for normality statistic suggested normality was not a reasonable assumption for the entire sample of Pre-CPT data ($SW = .966, df = 73, p = .044$). Since all of the Pre-CPT data were not normalized, an individual group test for normality was conducted. Based on the Shapiro-Wilk test of Pre-CPT, only the Co-Requisite data were normally distributed ($SW = .979, df = 25, p = .869$). The Intermediate Algebra ($SW = .890, df = 17, p = .047$) and Elementary Algebra ($SW = .904, df = 33, p = .007$) Pre-CPT data were not assumed to be normally distributed.

To determine if there were significant differences of mean Pre-CPT scores among the three groups of remediated mathematics students, Elementary Algebra, Intermediate Algebra and Co-Requisite College Algebra students, a one-way ANOVA test was conducted. The results of the Pre-CPT analysis indicated there was a significant difference among these groups ($F(2, 72) = 30.405, p < .001$). Since Pre-CPT data for two of the groups, Elementary and Intermediate Algebra, did not meet the normality assumption, a Kruskal-Wallis nonparametric test was also conducted. The results of this nonparametric test confirmed there was a significant difference among group mean Pre-

CPT scores ($\chi^2(2) = 36.195, p < .001$). Tukey HSD post hoc analyses were performed on all possible pairwise comparisons of mean Pre-CPT scores, to determine where statistically significant difference occurred (see Table 4.12).

Table 4.12

Tukey HSD - Multiple Comparisons of Differences in Mean Pre-CPT Mean Scores between Mathematics Remediated Groups

	EA	IA	CR
EA ($M = 33.12$)	-	-14.820*	-17.679*
IA ($M = 47.94$)		-	-.286
CR ($M = 55.80$)			-

Note. EA = Elementary Algebra, IA = Intermediate Algebra, CR = Co-Requisite College Algebra.

* $p < .05$.

As indicated in Table 4.12, the following groups were found to be significantly different at the .05 level: Elementary ($SD = 8.57$) compared to Intermediate ($SD = 11.73$) and Elementary ($SD = 8.57$) to Co-requisite ($SD = 7.95$). These results suggest the mean Pre-CPT scores for Elementary Algebra students were significantly lower than Intermediate Algebra and Co-Requisite College Algebra students. There were no significant differences between Intermediate Algebra and Co-Requisite College Algebra mean Pre-CPT scores.

Non-cognitive Characteristics

To gain an understanding of any differences in non-cognitive traits between the three groups of first-time freshmen mathematics students, data representing the means for

each non-cognitive characteristics (mindset, grit, and metacognitive awareness) were analyzed via ANOVA tests, to determine statistical differences.

Tests for homogeneity of variance and normal distribution were conducted prior to each ANOVA test. When one or both of these two assumptions were not met, a description of the procedures taken are included in the relevant sections below. The third assumption, independence, was met since individual participants each randomly enrolled in various mathematics courses based on their personal schedules, and they individually completed the online survey since it was sent to their personal email addresses.

Mindset. The mindset scores were tested for the homogeneity of variance assumption. This assumption was met according to Levene's test ($F(2,156) = 1.753, p = .177$). Normality was tested, with all groups meeting this assumption: Full Remediation ($SW = .962, df = 50, p = .112$), Part Remediation ($SW = .930, df = 26, p = .078$), and No Remediation ($SW = .970, df = 83, p = .051$). Figure 3 is a visual representation displaying the mindset means by group.

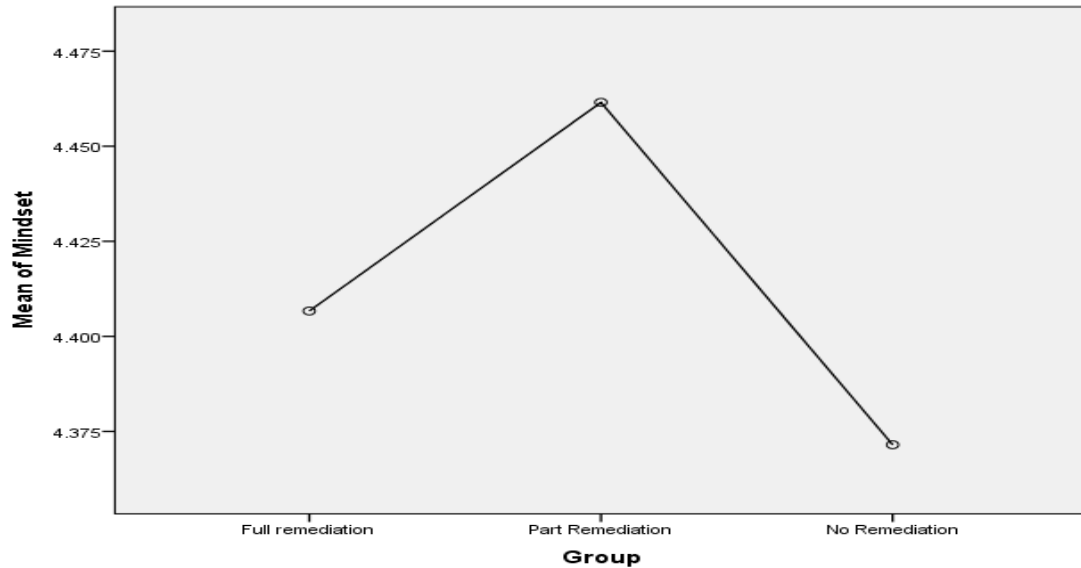


Figure 3. Means plot of mindset scores by group.

A one-way ANOVA test was conducted to determine significant differences among the mean mindsets of the three groups. The results ($F(2,156) = .093, p = .911$) indicated no significant differences in mean mindset scores among the groups, which suggests all first-time freshmen participants have equal views on the malleability of intelligence.

Grit. The grit scores met the homogeneity of variance assumption, as indicated by Levene's test ($F(2,156) = 1.020, p = .363$). Data for two of the three groups met the normal distribution assumption. This includes the Full-remediation group ($SW = .958, df = 50, p = .072$) and the Part-remediation group ($SW = .959, df = 26, p = .375$), but not the No-remediation group ($SW = .967, df = 83, p = .031$). A one-way ANOVA test was conducted to determine significant differences between the mean grit levels of the three groups. The results indicate there is a significant difference between groups ($F(2,156) =$

3.776, $p = .025$). Since the No Remediation group data did not meet the normality assumption, a Kruskal-Wallis nonparametric test was also conducted. The results of this nonparametric test confirmed there is a significant difference in mean ranks, i.e., rank order of the Grit score by group, ($\chi^2 (2) = 7.032, p = .030$). Post hoc analysis was conducted since significant differences were found by two tests. Table 4.13 displays the results of the Tukey HSD test on all possible pairwise comparisons of mean Grit scores.

Table 4.13

Tukey HSD - Multiple Comparisons of Differences in Mean Grit Scores between Groups

	Full	Part	No
Full ($M = 3.24$)	-	-.0101	-.3053*
Part ($M = 3.25$)		-	-.2952
No ($M = 3.55$)			-

* $p < .05$ level.

As indicated in Table 4.13, the following groups were found to be significantly different at the .05 level: Full-time remediated mathematics students ($SD = .65$) and Non-remediated math students ($SD = .72$). These results suggest students in a full-time remediation mathematics course were less gritty (lower perseverance and passion towards the completion of long term goals), compared to the participants enrolled in college-level non-remediated mathematics courses. The participants enrolled in a part-time remediated mathematics course were not significantly different than the other two groups.

Meta-cognitive Awareness. Data for Total MAI score for the three groups, met the normal distribution assumption: Full-remediation group ($SW = .972, df = 50, p = .274$), Part-remediation group ($SW = .958, df = 26, p = .362$), and the No-remediation

group ($SW = .987, df = 83, p = .601$). The MAI Total scores however, did not meet the homogeneity of variance assumption.

Knowledge of Cognition data did not meet the homogeneity of variance assumption, however it was normally distributed for each group: ($SW = .978, df = 50, p = .459$), Part-remediation group ($SW = .972, df = 26, p = .677$), and the No-remediation group ($SW = .976, df = 83, p = .121$). Regulation of Cognition data did not meet the homogeneity of variance assumption, however it was normally distributed for each group: ($SW = .981, df = 50, p = .607$), Part-remediation group ($SW = .959, df = 26, p = .366$), and the No-remediation group ($SW = .987, df = 83, p = .589$).

An ANOVA test was conducted to determine significant differences of mean MAI Total, Knowledge of Cognition, and Regulation of Cognition scores among the three groups. Since homogeneity of variances was not met, Welch's test was used to assess the equality of the means. The results indicate there is a significant difference in mean MAI Total among groups ($F(2, 59.144) = 3.795, p = .028$) and in mean Knowledge of Cognition among the groups ($F(2, 59.243) = 7.020, p = .002$). As for Regulation of Cognition, there were no significant differences found among group means ($F(2, 60.709) = 2.305, p = .108$).

Since all metacognitive category data were not homogeneous, Dunnett T3 post hoc analyses were performed (see Table 4.14) to determine where the differences in groups occurred.

Table 4.14

Dunnnett T3 Multiple Comparisons of Mean Differences in Metacognition between Groups

Dependent Variable	(I) Group	(J) Group	Mean Differences (I-J)	SE	p
MAI Total	Full	Part	-4.588	8.234	.924
		No	-15.123*	5.917	.037*
	Part	Full	4.588	8.234	.924
		No	-10.536	6.920	.351
	No	Full	15.123*	5.917	.037
		Part	10.536	6.920	.351
K of C	Full	Part	-1.189	2.776	.963
		No	-6.396*	1.841	.002*
	Part	Full	1.189	2.776	.963
		No	-5.201	2.468	.120
	No	Full	6.396*	1.841	.002*
		Part	5.201	2.468	.120
R of C	Full	Part	-3.398	5.729	.910
		No	-8.727	4.298	.130
	Part	Full	3.398	5.729	.910
		No	-5.329	4.744	.602
	No	Full	8.727	4.298	.130
		Part	5.329	4.744	.602

Note. K of C = Knowledge of Cognition; R of C = Regulation of Cognition.

* $p < 0.05$.

Total MAI score is the sum of the knowledge of cognition and regulation of cognition sub-components. As Table 4.14 indicates, the mean MAI Total scores for the students' not needing remediation were significantly higher than students in a full-time remediated mathematics course, which implies students not needing mathematics remediation had more knowledge of how they learn and how to regulate their learning,

compared to full-time remediated mathematics participants. Part-time remediated student means were higher than the full-time remediated students as well, and were lower than the non-remediated group means, however they were not significantly higher or lower than these groups.

When considering the two sub-components individually, the results also indicate the mean Knowledge of Cognition scores for the students' not needing remediation were significantly higher than students in a full-time remediated mathematics course. This suggests college-level mathematics students know more about their own learning including strategies and conditions that strategies work, as compared to the full-time remediated mathematics participants. Part-time remediated student means were higher than the full-time remediated means, and lower than the non-remediated student means, however they were not significantly different than either group.

As for Regulation of Cognition, there were no significant differences found between group means. Participant knowledge of how to plan, monitor, and evaluate their learning were not significant based on group means.

Predictors of the Academic Achievement of First-time Freshmen Mathematics Students

Before determination of the predictive nature of the numerous variables on participant academic achievement, an understanding of how each group of students, full-time, part-time and no remediation, performed academically in their mathematics courses, was initiated. Final course letter grades were collected, for each group of participants, from University records. Group means were calculated based on the 4.0

scale, with A = 4.0, B = 3.0, etc. A score of 0 (zero) was assigned to students who failed, withdrew or did not complete their mathematics course. Table 4.15 displays the mean course grades for each of the three groups of student participants.

Table 4.15

Descriptive Statistics for Final Course Letter Grades – By Remediation Group

Group	<i>n</i>	<i>M</i>	<i>SD</i>
Full-time	50	2.78	1.33
Part-time	26	2.92	.98
No	83	3.45	.93

The sample mean final letter grades were higher for students not in a remediated mathematics course as compared to the part-time remediated mathematics students, and this group had higher final letter grades on average than the students enrolled in a full-time remediation mathematics course.

With differences emerging, after determining the final grade descriptive statistics for each group of first-time freshmen mathematics participants, the next task was to determine if there were statistically significant differences between the groups. Thus, the researcher analyzed the data for differences using an ANOVA test.

Final course letter grades were first tested for the homogeneity of variance and normal distribution assumptions. The homogeneous assumption was not met according to Levene's test ($F(2,156) = 3.388, p = .036$), nor was the normality assumption ($SW = .848, df = 159, p < .001$). Since the two assumptions were not met, a Kruskal-Wallis nonparametric test was conducted to determine if mean ranks were significantly different. The results of this nonparametric test confirmed there were significant differences

between group final course grades ($\chi^2 = 14.539$, $df = 2$, $p = .001$). Post hoc analysis was conducted since a statistically significant difference was found. Since equal variances were not assumed, Dunnett's T3 test was performed on all possible pairwise comparisons of course letter grade averages by group. The following groups were found to be significantly different at the .05 level: Full-time remediated mathematics students ($M = 2.78$, $SD = 1.33$) compared to Non-remediated mathematics students ($M = 3.45$, $SD = .93$). These results suggest the mean final course letter grades for no-remediation students were significantly higher than students enrolled in a full-time remediated mathematics course. Part-time remediated students were not significantly different than either group.

With at least two groups having significantly different final grade averages, the next focus was to determine correlations between the academic achievement of the first-time freshmen groups of mathematics students and their demographic, precollege cognitive, and non-cognitive self-reported characteristics. To answer the third research question regarding the predictive nature of the characteristic variables (demographic, high school cognitive data, mindset, grit, and metacognition) on academic achievement as measured by final mathematics course letter grades, the researcher conducted a two-tailed, bivariate analysis which resulted in Pearson-product moment correlation coefficients (r). The r coefficient, which can range from 0 to ± 1 , looks at the strength and direction, positive or negative, of the relationship between variables. If the relationship is positive, then as one variable increases, the other increases as well. When r is squared, (denoted r^2), and multiplied by 100, the shared variance is determined, and this signifies how much the two variables have in common (Ary, et al., 2006).

Since the number of part-time remediation participants was only 25, it was decided to combine full and part-time remediated students into one group ($n = 76$), which was subsequently *Any Remediation*, going forward. This decision was made based on what Ary, et al, stated “You should be very careful in attaching too much importance to large correlations when small sample sizes are involved; an r found in a small sample does not necessarily mean that a correlation exists” (2006, p. 384).

Correlational analysis was therefore performed on each group, *Any Remediation* and *No Remediation* to determine relationships between Final Grades and the other variables in the study: High School GPA, ACT scores, Mathematics placement scores, demographic data, mindset, grit, and metacognitive awareness and its sub-scales. For purposes of displaying the results in this chapter, categories were created for correlational analyses for each mathematics group: specifically demographic (gender, ethnicity, job status, and parent’s education), precollege (High School GPA, ACT scores, Mathematics placement scores), and non-cognitive (Mindset, Grit, MAI total, Knowledge and Regulation of Cognition) sets of variables.

Any Remediation Final Grades and Demographics. Firstly, correlational analysis regarding demographic characteristics and final grades, was conducted on the group of participants that required any level of mathematics remediation. Displayed in Table 4.16, are the Pearson product-moment correlation coefficients, which indicate relationships between demographic variables and final letter grades for the *Any Remediation* group.

Table 4.16

Correlation Analysis: Demographic Variables of the Any Remediation Group

Variable	FG	Gen	Ethnicity	Job	MomCol
Gen	.212	-			
Ethnicity	.317**	-.131	-		
Job	.048	.057	.101	-	
MomCol	-.108	-.033	.010	.148	-
DadCol	.079	-.053	-.034	-.076	.258*

Note. FG = Final Grade, Gen = Gender, MomCol = Mother attended College, DadCol = Father attended College.

* $p < .05$. ** $p < .01$.

A statistically significant positive correlation was found between ethnicity and final grades ($r = .317$, $n = 76$, $p = .005$), which indicated a 10% shared variance. According to Cohen (1988), an $r = .30$, for the Behavioral Science would represent a medium effect. Additionally, though not significant, there was a low positive correlation between gender and final grades ($r = .212$, $n = 76$, $p = .066$).

Any Remediation Final Grades and Precollege Variables. Displayed in Table 4.17, are the Pearson product-moment correlation coefficients, which indicate relationships between precollege variables (HSGPA, ACT-M, and ACT-C), placement test scores (Pre-CPT, PostCPT, and CPT Δ) and final letter grades for the groups that required some remediation, the Full-time and Part-time remediation groups.

Table 4.17

Correlation Analysis: Precollege Cognitive, Placement Variables and Any Remediation

Variable	FG	HSGPA	ACT-M	ACT-C	Pre-CPT	PostCPT
HSGPA	.084	-				
ACT-M	-.009	.042	-			
ACT-C	-.045	.178	.456**	-		
Pre-CPT	.084	.160	.180	.214	-	
PostCPT	.299*	-.011	.165	.378**	.613**	-
CPTΔ	.295*	-.143	.063	.287*	-.075	.742**

Note. FG=Final Grade, HSGPA=High School GPA, ACT-M=Mathematics ACT sub-score, ACT-C=Composite ACT score, Pre-CPT=Pre-Computer Placement test score, PostCPT= Post Computer Placement test score, CPTΔ - CPT change score.

* $p < .05$. ** $p < .01$.

The results indicate a significant correlation between Post-CPT placement scores and final letter grades ($r = .299$, $N = 73$, $p = .010$), which indicates an 8.9% shared variance, which is very close to being moderately strong. Additionally, there was a significant correlation between CPT change scores and final letter grades ($r = .295$, $N = 73$, $p = .011$), which indicates an 8.7% shared variance. The variables Post-CPT and CPT Change were highly significantly correlated ($r = .742$, $N = 73$, $p < .001$) which suggests the variables are collinear. Multicollinearity occurs when two variables correlate at an extremely high level, and the inclusion of both variables in a regression may produce misleading results (Keith, 2006). Therefore, during the ensuing regression analysis, only one of these variables will be included. For the same reason, since ACT Mathematics and ACT Composite highly correlated ($r = .456$, $N = 67$, $p < .001$), as well as Pre-CPT

and Post CPT ($r = .613$, $N = 73$, $p < .001$) only one from each of these sets of variables will be included in the ensuing regression.

Any Remediation Final Grades and Non-Cognitive Variables. Displayed in Table 4.18, are the Pearson product-moment correlation coefficients between non-cognitive variables (mindset, grit, MAI Tot, K of C, and R of C) and final grades for the groups that required some remediation, the Full-time and Part-time mathematics remediation groups. Also displayed (diagonally in bold) in the table are the reliability coefficients for each non-cognitive instrument.

Table 4.18

Correlation Analysis: Non-Cognitive Variables and Any Remediation

Variable	FG	Mindset	Grit	MAITot	K of C	R of C
Mindset	.185	.87				
Grit	.337**	.336**	.801			
MAITot	.211	.415**	.524**	.956		
K of C	.269*	.322**	.535**	.935**	.905	
R of C	.176	.436**	.497**	.987**	.867**	.943

Note. The coefficients on the diagonal in bold are the Cronbach alpha of each scale.

Note. FG=Final Grade, MAITot=Total Metacognitive Awareness, K of C=Knowledge of Cognition, R of C=Regulation of Cognition.

* $p < .05$. ** $p < .01$.

The results of the correlational analysis between non-cognitive traits and final letter grades, indicated a significant correlation between mean grit scores and final course letter grades ($r = .337$, $n = 76$, $p = .003$), with an 11.4% shared variance, which is considered medium in strength. Knowledge of Cognition was also significantly

correlated with final letter grades ($r = .269, n = 76, p = .019$), which indicates a low, 7.2%, shared variance. The variables of total MAI, Knowledge of Cognition and Regulation of Cognition were excessively collinear, by indication of their correlation coefficients between the variables, which ranged from $.867 < r < .987$, and p -values $< .001$. Also of interest, grit was significantly correlated with all non-cognitive variables (range of r was $.336 - .535$ and all p -values $< .004$). Though mindset was not correlated with final letter grades, it was significantly correlated with all other non-cognitive variables, with r -coefficients ranging from $.332 - .436$ (p at most = $.003$). Logically then, MAI total was also significantly correlated with mindset and grit. Because of the extreme collinearity between MAI Total, Knowledge of Cognition, and Regulation of Cognition, only one of these variables was included in the ensuing regression analysis.

In summary, for the set of students enrolled in a course requiring any level of mathematics remediation, the following characteristic variables were significantly correlated with final grades: ethnicity, Post-CPT test scores, CPT Δ (Change in Pre- and Post-CPT scores), grit, and knowledge of cognition. Though not significant, gender and total metacognitive awareness had low positive correlations with final grades for this sample of remediated mathematics students.

No Remediation Final Grades and Demographics. For the students *not* enrolled in a mathematics course requiring remediation, Table 4.19, displays the correlation coefficients indicating relationships between demographic variables and final letter grades for this group of participants enrolled in college-credit level mathematics classes (*No Remediation*).

Table 4.19

Correlation Analysis: Demographic Variables and No Remediation

Variable	FG	Gen	Ethnicity	Job	MomCol
Gen	.019	-			
Ethnicity	.016	-.008	-		
Job	.188	.104	-.055	-	
MomCol	.146	-.081	.018	-.027	-
DadCol	.193	-.007	.174	.135	.397**

Note. FG = Final Grade, Gen = Gender, MomCol = Mother attended College, DadCol = Father attended College.

* $p < .05$. ** $p < .01$.

There were no statistically significant correlations found between any demographic variable and final grades for this sample of students not enrolled in a course requiring mathematics remediation. The only variable nearing, but not reaching statistical significance, was Father's educational attainment ($r = .193$, $n = 83$, $p = .080$). Of interest, there was a significant relationship between the mother and father college variables ($r = .397$, $n = 83$, $p < .001$), which is on the upper medium strength ($r^2 = 15.8\%$) of shared variance.

No Remediation Final Grades and Precollege Variables. Displayed in Table 4.20, are the Pearson product-moment correlation coefficients indicating relationships between precollege variables (HSGPA, ACT-M, and ACT-C) and final grades for the group not requiring mathematics remediation.

Table 4.20

Correlation Analysis: Precollege Cognitive Variables and No Remediation

Variable	FG	HSGPA	ACT-M
HSGPA	.247*	-	
ACT-M	.268*	.072	-
ACT-C	.122	-.078	.696**

Note. FG=Final Grade, HSGPA=High School GPA, ACT-M=Mathematics ACT sub-score, ACT-C=Composite ACT score.

* $p < .05$. ** $p < .01$.

The results indicated a significant positive correlation between High school GPA and final grades ($r = .247, n = 81, p = .026$), which indicates a 6.2% shared variance, which is low in strength. Additionally, there was a significant correlation between ACT Mathematics sub-scores and final grades ($r = .268, n = 82, p = .015$), which indicates a low to moderate 7.2% shared variance. The ACT scores, composite and mathematics sub-score, were collinear ($r = .696, n = 82, p < .001$). Therefore, during the ensuing regression, only one of these variables was included.

No Remediation Final Grades and Non-Cognitive Variables. Displayed in Table 4.21, are the correlation coefficients between the non-cognitive variables (Mindset, Grit, MAI Tot, K of C, and R of C) and final grades for the non-remediation group (*No Remediation*) of first-time freshmen mathematics participants.

Table 4.21

Correlation Analysis: Non-Cognitive Variables and No Remediation

Variable	FG	Mindset	Grit	MAITot	K of C	R of C
Mindset	.063	.874				
Grit	.425**	.076	.801			
MAITot	.177	.353**	.257*	.956		
K of C	.211	.297**	.336**	.843**	.905	
R of C	.143	.341**	.193	.968**	.680**	.943

Note. The coefficients on the diagonal in bold are the Cronbach alpha of each scale.

Note. FG=Final Grade, MAITot=Total Metacognitive Awareness, K of C=Knowledge of Cognition, R of C=Regulation of Cognition.

* $p < .05$. ** $p < .01$.

The results of the correlational analysis between non-cognitive traits and final grades, indicate a significant positive correlation between mean Grit scores and final grades ($r = .425$, $n = 83$, $p < .001$), with an 18.1% shared variance, which is considered on the high end of medium strength. Though Knowledge of Cognition was not quite significantly correlated with final letter grades ($r = .211$, $n = 83$, $p = .055$), it had a low positive correlation, with a 4.4% shared variance. Mindset was not correlated with grit, however it was correlated with MAI total and its sub-components Knowledge and Regulation of Cognition, as indicated by r-coefficients ranging from .297-.343 (p -values $< .007$). Grit was correlated with total MAI and Knowledge of Cognition ($.257 < r < .353$, and p -values $< .007$). Also of note, MAI total was significantly correlated with all non-cognitive variables (range of r was .257 - .968 and all p -values $< .020$). MAI Total was excessively correlated with Knowledge of Cognition and Regulation of Cognition

(.843 < r < .968, p < .001) indicating collinearity, therefore only one of these variables will be included in the ensuing regression analysis.

In summary, for the set of students *not* enrolled in a course requiring mathematics remediation, the following characteristic variables were significantly correlated with final grades: high school GPA, ACT mathematics score, and grit. There were no demographic variables found to be correlated with final grades. For this group of students, though not significant, father's educational attainment had a low positive correlation with final grades; as did knowledge of cognition, a non-cognitive characteristic.

Investigation of the Predictors of Academic Achievement

After the correlational analysis, the study aimed to determine which variables (demographic, precollege, and/or non-cognitive) predicted academic achievement. To accomplish this, hierarchical multiple regression tests were performed to determine the best combination of independent variables that predict academic achievement, as measured by final grades (on a 4.0 scale). For each group, *any remediation* and *no remediation*, demographic variables (gender, ethnicity, and parent's education) were the first block of variables entered into the linear regression, followed by the precollege variables, and lastly entered were the block of non-cognitive variables. This order was selected based on the participant's actual natural procession through the years. Meaning student's gender, ethnicity, and likely their parental education were established before high school, and though the non-cognitive variables could have been developed in, or even before high school, these variables were collected while the students were in college. "One common and defensible solution is to input the variables in order of

presumed or actual time precedence” (Keith, 2006, p. 80-81). Job status was not included in the regression, for it did not correlate with grades, and there were no significant differences found between the percent of students working within each level of remediation group. Post-CPT scores were omitted from the regression since participants scores on this test were required to contribute towards the calculation of final grades, for the students in any remediation course. Also, for variables that were determined to be collinear by the correlational tests, only one of each set of collinear variables have been entered into the following regression tests.

Linear Regression: Any Remediation

For the full-time and part-time consolidated group of participants, indicated as *Any Remediation*, the correlational analysis determined ACT-Composite and ACT Mathematics sub-scores were collinear, and since this study was in regards to mathematics, the ACT-mathematics sub-score was included in the linear regression, instead of the composite score. Also collinear were all metacognitive variables. Knowledge of Cognition was the only variable significantly correlated with grades, therefore it was included in the regression analysis. Table 4.22 presents the results when final grades were regressed on demographic variables, which were entered first, followed by precollege variables second, and non-cognitive characteristics which were entered last.

Table 4.22

Hierarchical Regression of Demographic, Precollege and Non-cognitive variables on Final Grades for the Remediation Group of Students

Variable	<i>B</i>	SE(<i>B</i>)	β	ΔR^2
Block 1				.123
Gender	.481	.309	.188	
Ethnicity	-.553*	.276	-.242	
DadCol	-.272	.292	-.114	
MomCol	.148	.275	.065	
Block 2				.014
Gender	.445	.335	.174	
Ethnicity	-.581*	.285	-.254	
DadCol	-.285	.302	-.120	
MomCol	.176	.282	.078	
Pre-CPT	.008	.012	.085	
ACTMath	-.037	.131	-.037	
HSGPA	.238	.377	.078	
Block 3				.178**
Gender	.387	.311	.152	
Ethnicity	-.644*	.264	-.282	
DadCol	-.204	.277	-.086	
MomCol	.212	.265	.094	
Pre-CPT	.009	.011	.091	
ACTMath	-.017	.121	-.016	
HSGPA	.074	.348	.024	
Mindset	-.027	.153	-.022	
Grit	.656**	.231	.375	
KofC	.010	.013	.105	

Note. Total $F(3,57)$ for Block 3 = 4.929, Adjusted $R^2 = .194$.

* $p < .05$. ** $p < .01$.

The results of the analysis are shown in Table 4.22. The first block of variables entered into the regression, demographics, did not quite result in a statistically significant

increase in explained variation in final grades ($\Delta R^2 = .123$, $F(4, 63) = 2.206$, $p = .078$).

Understanding the demographic makeup of students, though found to be not quite statistically significant, may be an important focus, when considering their mathematics achievement in academics. Adding the second block, precollege cognitive variables, into the regression resulted in a positive change, though it was not a significant increase in explained variance ($\Delta R^2 = .014$, $F(3, 60) = .323$, $p = .809$). Of interest are the results of the variables mindset, grit, and knowledge of cognition, being entered in as the third block of the regression. These non-cognitive variables explained a statistically significant increase in the variance of final course grades ($\Delta R^2 = .178$, $F(3, 57) = 4.929$, $p = .004$). These findings suggest that the non-cognitive variables of students requiring remediation, may be important for their academic achievement, as measured by course grades.

However when all variables were included in the last stage of the regression, the final model explained 19.4% of the variance in final grades. In this model there were two individual predictors of final grades, ethnicity ($B = -.582$, $p < .05$), and grit ($B = .656$, $p < .01$). These significant regression findings, confirm with the correlational analysis, that these two variables, ethnicity and grit, may influence a student's academic success. No other variables in the regression were significant predictors of academic achievement for this group of students requiring mathematics remediation.

Linear Regression: No Remediation

For those participants not in a mathematics course requiring remediation (*No Remediation*), correlation analysis determined ACT-Composite and ACT Mathematics sub-scores were collinear, and again, since this study was in regards to mathematics, the ACT-Mathematics sub-score was included in the regression, instead of the composite score. All metacognitive variables were also collinear for this group of students, so to be consistent with the *Any Remediation* group, Knowledge of Cognition was the variable included in the regression. This group of students did not take the CPT, therefore that variable is excluded. Job status was also excluded for similar reasons mentioned in the earlier regression. Blocks of variables were entered into the regression, similarly to the *Any Remediation* group, for consistency purposes. Table 4.23 presents the results when final grades were regressed on demographic, precollege variables, and non-cognitive variables in a hierarchical test.

Table 4.23

Hierarchical Regression of Demographic, Precollege and Non-cognitive variables on Final Grades for the No Remediation Group of Students

Variable	<i>B</i>	SE(<i>B</i>)	β	ΔR^2
Block 1				.052
Gender	-.083	.242	-.038	
Ethnicity	.034	.215	.018	
DadCol	-.327	.230	-.176	
MomCol	-.179	.235	-.093	
Block 2				
Gender	-.052	.243	-.024	.139*
Ethnicity	.075	.208	.040	
DadCol	-.229	.232	-.123	
MomCol	-.056	.233	-.029	
ACTMath	.061	.036	.203	
HSGPA	.530	.269	.222	
Block 3				.323**
Gender	-.116	.224	-.054	
Ethnicity	.159	.191	.084	
DadCol	-.287	.211	-.154	
MomCol	.083	.215	.043	
ACTMath	.044	.034	.144	
HSGPA	.519*	.245	.218	
Mindset	.003	.116	.003	
Grit	.530**	.137	.407	
KofC	.010	.012	.089	

Note. Total $F(3, 71)$ for Block 3 = 6.459, Adjusted $R^2 = .237$.

* $p < .05$, ** $p < .01$.

The results did not indicate a statistically significant increase in variance when demographic variables were entered into the regression ($\Delta R^2 = .052$ $F(4, 76) = 1.038$, p

= .393). This suggests demographic variables may not predict academic achievement for college-level mathematics participants. Introducing the second block of variables, high school GPA and ACT mathematics scores (precollege cognitive variables) into the regression, resulted in a significant positive increase in explained variance ($\Delta R^2 = .069$, $F(2, 74) = 3.727$, $p = .029$). Collectively, the first two blocks of variables accounted for 13.9% of the variation in final grades. The non-cognitive variables mindset, grit and knowledge of cognition, were entered in as the third block of the regression. As a result of this insertion, a significant increase in variance was realized ($\Delta R^2 = .185$, $F(3, 71) = 6.459$, $p = .001$), which may suggest that the non-cognitive variables of college-level mathematics students may also be an important predictor of academic achievement.

When all variables were included in the last stage of the regression, the final model explained 23.7% of the variance in final grades. In this model there were two significant predictors for this group of college-ready students, high school GPA ($B = .519$, $p < .05$), and grit ($B = .530$, $p < .01$). These two regression findings, reconfirm with the correlational analysis, that these two variables, high school GPA and grit, may influence a student's academic success. No other variables were significant predictors of academic achievement for this group of students requiring mathematics remediation.

Retention of First-time Freshmen Students Enrolled in Mathematics Courses Having a Remediation Component

The final phase of the study focuses on the retention rates of the group of student participants enrolled in either a full-time remedial mathematics course or the part-time co-requisite algebra course. Retention is a dichotomous categorical variable, whereby

either a student reenrolled the next semester or they did not reenroll at the university. Before answering the fourth research question, which addresses the predictive nature of the characteristic variables (demographic, high school cognitive data, mindset, grit, and metacognition) on the retention of the mathematics remediation participants, descriptive statistics, including a chi-squared test of independence were conducted. Initially, retention was analyzed by comparing percentages of participants who returned to the university the following semester (Spring 2017), to students not retained, for the two types of remediation groups, and the *Any Remediation* group which represents the total of all mathematics remediation students. Table 4.24 displays the retention percentages by group.

Table 4.24

Retention Percentages by Group

	Returned <i>n</i> (%)	Did Not Return <i>n</i> (%)	Total <i>n</i> (%)
Full Remediation	44 (88.0)	6 (12.0)	50 (100)
Part Remediation	25 (96.2)	1 (3.8)	26 (100)
Any Remediation (Total)	69 (90.8)	7 (9.2)	76 (100)

The relation between retention and mathematics groups were individually subjected to the chi-square test of independence, and the results revealed there was no significant difference found between Full Remediation and Part remediation groups and the percent of students retained ($\chi^2 (1) = 1.360, p = .244$). Another way to state this is to

say that retention and remediation requirements are independent of each other, which suggests the proportion of retained students in each mathematics remediation group were similar. Nearly 90% of all participants in each group came back to the university the next semester (see Table 4.24). Though there is not enough evidence to suggest an association between retention and mathematics remediation group, it can be stated that the full remediation group of students had the highest percent of students not returning to school during the ensuing Spring 2017 semester (see Table 4.24).

Investigation of the Predictors of Retention

With the retention rates of the two individual groups of remediation students being similar (Full and Part not significantly different), the study proceeded to use the total sample of remediation participants, *Any Remediation* ($n = 76$), to conduct the next analysis. This part of the study aimed to determine which variables (demographic, cognitive, and/or non-cognitive) predict the retention of mathematics remediation students. To accomplish this, a logistic regression test was performed since the dependent variable retention, is categorical. According to Leech et al. (2011), “logistic regression is helpful when you want to predict a categorical variable from a set of predictor variables” (p. 129). The demographic, cognitive, and non-cognitive variables were entered in as independent variables. As discussed in previous data analyses, only one variable that is collinear with another (those with high correlations) was included as a predictor variable. As such, total metacognitive awareness was entered into the regression instead of both Knowledge and Regulation of Cognition. Similarly, ACT

Mathematics and Post-CPT scores were included instead of ACT-Composite, Pre-CPT and CPT Change scores, due to multicollinearity.

Due to the small sample size ($n = 76$) in relation to the number of predictor variables, the logistic regression was run first with the demographic variables, followed by the cognitive variables, and lastly with the non-cognitive variables as predictors of retention. The results of the first logistic regression determined whether the five demographic variables, *gender*, *ethnicity*, *job status*, *father*, and *mother's college attendance* significantly predicted retention. When all of these variables were considered together, the model did not significantly predict whether or not a student was retained the next semester ($\chi^2 = 2.68$, $df = 5$, $p = .749$). Table 4.25 presents the odds ratios, which suggests the odds of remediated mathematics students being retained cannot be predicted by any demographic information (all five p values $> .175$).

Table 4.25

Logistic Regression: Demographics Predicting Retention

Variable	<i>B</i>	<i>SE</i>	<i>Odds ratio</i>	<i>p</i>
Gender	.07	.90	1.07	.940
Ethnicity	-.48	.89	.62	.593
Job Status	.27	.83	1.31	.749
DadCol	.11	.94	1.11	.908
MomCol	-1.26	.93	.29	.175
Constant	3.07	1.30	21.60	.018

Note. DadCol = Father attended College, MomCol = Mother attended College.

The cognitive variables, *high school GPA*, *ACT-Mathematics* and *Post-CPT scores*, were the next set of variables entered together into the regression, to determine their predictability of mathematics remediation student retention. The results indicate that the model that includes all 3 cognitive variables, significantly predicted the retention of the mathematics remediation participants ($\chi^2 = 11.84$, $df = 3$, $p = .008$). Table 4.26 displays the odds ratios, which suggest that the odds of being retained, if you were a mathematics remediation student, are increasingly greater as Post-CPT scores increase.

Table 4.26

Logistic Regression: Cognitive Variables Predicting Retention

Variable	<i>B</i>	<i>SE</i>	<i>Odds ratio</i>	<i>p</i>
HSGPA	-.08	1.55	.92	.960
ACT-M	.23	.45	1.26	.605
Post-CPT	.12	.05	1.13	.022
Constant	-7.18	9.07	.00	.429

Note. HSGPA=High School GPA, ACT-M=Mathematics ACT sub-score.

Lastly, the non-cognitive variables, *mindset*, *grit* and *total metacognitive awareness*, were input into the logistic regression as the independent variables. When these three variables were considered together, the model significantly predicted whether a student was retained, or was not retained the next semester ($\chi^2 = 11.26$, $df = 3$, $p = .010$). Table 4.27 presented the odds ratios, which suggests the odds of remediated mathematics students being retained increases as Total Metacognitive Awareness increases. Also of note, *grit* ($p = .047$) and *total metacognitive awareness* ($p = .002$) were

individually, significant predictors of whether a mathematics remediation student reenrolled the following semester.

Table 4.27

Logistic Regression: Non-Cognitive Variables Predicting Retention

Variable	<i>B</i>	<i>SE</i>	<i>Odds ratio</i>	<i>p</i>
Mindset	-.54	.61	.58	.379
Grit	.38	.83	1.46	.649
MAI-Tot	.04	.02	1.05	.016
Constant	-3.52	2.74	.03	.199

Note. MAI-Tot=Total Metacognitive Awareness.

In summary, the regression analysis reconfirmed with the correlational analysis, that Post-CPT scores may influence student retention. Additionally this analysis determined metacognitive awareness predicted the retention of remediated mathematics students. With total metacognitive awareness and knowledge of cognition being collinear variables (see Table 4.21), one might suggest this reconfirms that knowing how one learns may determine whether one continues on with college. While ethnicity was correlated with academic achievement, it did not predict retention. No other variables were significant predictors of retention for this group of students requiring mathematics remediation.

Chapter 5 contains a discussion of the results of the analyses. A summary of the findings, implications from the study and recommendations for future research are also addressed.

CHAPTER V

CONCLUSION

Universities are inherently interested in the academic achievement, retention and eventual graduation of all students enrolled at their institutions. Academically under-prepared students have historically had less academic success in college and have left college at higher rates, as compared to those students not requiring remediation; thus, universities and researchers have called for more studies focusing on factors that impact the success of students enrolled in college remediation classes (CCA, 2012).

Research on the demographic factors of first time freshmen, such as gender, ethnicity, and parental education have been conducted for decades and results have indicated that college freshmen today are more diverse than in the past (NCES, 2015). Precollege academic performance indicators (e.g., high school grade point averages and ACT scores) of first time freshmen and their impact on academic achievement is another important research topic. Research has also suggested that non-cognitive characteristics of students, such as mindset, grit, and metacognition may also influence the academic success of students (Easton, 2013). This current study adds to this collection of research, as it uniquely considers how all three indicators for success, demographic, cognitive, and non-cognitive traits, relate to the academic achievement and the retention of first-time

freshmen students enrolled in various levels of mathematics at a rural Midwestern regional university.

The first objective of this quantitative survey-design study was to describe key characteristics of first-time freshmen college students enrolled in three levels of mathematics, including full-time remediation, part-time remediation, and non-remediated college-level mathematics courses at the Midwestern university. Second it was to determine differences in characteristics among the three groups/levels of mathematics students. The last set of goals for this study were to determine relationships between the academic achievement of all mathematics student participants and their demographic, cognitive and non-cognitive characteristics as well as the retention of students needing remediation and the noted key characteristics.

This study used student self-reported survey responses and university records to extract student demographic, cognitive and non-cognitive information. Quantitative data analyses, including inferential statistics, correlational, and regression analyses were utilized to answer the following four research questions:

1. What are the characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of college freshmen enrolled in their first college mathematics course at a Midwest regional university?
2. Are there significant differences in demographic, cognitive, and non-cognitive traits (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) between

groups (Full remediation, part remediation and no remediation) of college freshmen based on mathematics course enrollment?

3. Which characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of college freshmen enrolled in their first college mathematics courses at a Midwest regional university, are predictors of academic achievement as measured by final letter grades?
4. Which characteristics (i.e., High School GPA, ACT and Mathematics placement scores, demographic, mindset, grit, and metacognitive awareness) of freshmen students enrolled in a mathematics course requiring remediation at a Midwest regional university, are predictors of retention?

This chapter includes a discussion of the findings of each research question, based on the data analyses, and how the findings relate and add to the literature reviewed. The first phase of data collection for this study addressed the first two research questions, thus the discussion in this chapter begins with a description of the key characteristics of the all first-time freshmen mathematics participants at a Midwestern university, and continues with a discussion on the main differences among the participants enrolled in the three different levels of mathematics courses. Discussions then focus on the academic achievement of freshmen participants in their mathematics classes, and how the results add to the current literature. Lastly, a retention discussion ensues.

Discussion on the Characteristics of First-time Freshmen Students in Math Courses

Who are the participants at this rural Midwestern regional University? To gain an

understanding of the first-time freshmen students enrolled in various levels of mathematics courses, participants took an online survey which yielded traditional demographic data (gender and ethnicity), parental educational levels, employment status information, and non-cognitive traits. From university records, age and pre-collegiate cognitive performance indicators (high school grade point average, ACT composite and mathematics scores, and mathematics placement test scores for students not meeting university entrance requirements) were ascertained. The following discussion summarizes key demographic, precollege, and non-cognitive findings of all participants in the current study.

Key Demographics. Based on recent national and statewide statistical reports regarding students in college and universities, the demographic nature of all participants in the current study, represent a unique group of first-time freshmen. For example, gender differences in this study were large, as there were nearly three times as many first-time freshmen female participants as there were male participants. The 74.2% female percentage figure found in this study, is more than 15% higher than recent national and state reported statistics on gender (NCES, 2016; OSHRE, 2015). As for age, 88.1% of all participants were 18-19 years of age, with 3.1% being 25 years old or older, which means there were first-time freshmen participants who were nontraditional (i.e., not straight out of high school). Having non-traditional students in the current study helps add to the research on this the growing population of older students who enter college each year.

The ethnic composition of the group of students completing the survey also greatly varied from national and in-state statistical reports. While one-third of all students enrolled at the current university (setting for the study) are Native American,

24.5% of the sample were Native American students, which was second only to Caucasian students (47.2%) in percent representation in this study. The Native American population rate for the current study, is 25 times higher than the 2015 national percentages reported in the *Condition of Education* summary (NCES, 2017) which indicated less than 1% of the undergraduates in postsecondary institutions in the U.S. were Native American. At this rural Midwestern regional university this Native American freshmen participant percent was also more than 3 times higher than the statewide 7.8% Native American post-secondary school student population (OSHRE, 2015). Additionally there were nearly 3 times as many students classifying themselves as of multi-racial decent (17.6%), compared to the in-state 7.1% rate (OSHRE, 2015). Lastly of note, the percent of participant fathers (46.6%) attaining at most a high school diploma or GED, roughly equaled the percent of mothers (45.9%) earning a college degree (associates, bachelor's or higher). This may suggest a high school senior's decision to enroll in college depends on the gender and educational attainment of the parent?

Key Precollege Cognitive Findings. Discussed here are the key findings of the high school related cognitive abilities of the participants prior to college, specifically high school GPA, ACT Composite and ACT-Mathematics scores. Of interest, for this entire group of first-time freshmen participants enrolled in various levels of mathematics classes, their mean high school grade point average ($M = 3.43$) appeared to be higher than the entire statewide senior mean high school GPA ($M = 3.07$) (OSHRE, 2015).

Average ACT mathematics scores for the all participants in the study ($M = 19.5$), were lower than the national average ($M = 20.8$) ACT mathematics score, and only

slightly lower than the reported (OSHRE, 2015) in-state average ACT mathematics scores of seniors ($M = 19.8$). The mean ACT composite score of the participants ($M = 20.7$) was between the national average 20.8, and the state average was 20.4 (OSDE, 2016). In the Midwestern state of the current study, students that score below 19 on the mathematics portion ACT often require remediation, thus the participant average being so close to this remediation cutoff score, implies an ample number of students enrolled in college remediation classes. In the current study nearly half of the participants (47.8%) were enrolled in either full-time or part-time mathematics remediation. The state in which the current study was conducted, published the *Remediation Report* (OSHRE, 2017) indicating the percent of the first-time freshmen students who enrolled in at least one developmental mathematics course, during the 2015-2016 semester. Statewide institutions had 32.5 % of the entering freshmen class enrolled in a mathematics remediation course, while it was 34.2% for the regional university system.

Key Non-Cognitive Findings. Beside past cognitive ability, researchers suggest students have non-cognitive or innate skills, or can develop such skills, that enable students to learn, achieve, and be successful (Dweck, et al., 2011; Garcia, 2014; Tough, 2012). The non-cognitive characteristics in this study that do not measure academic achievement (i.e., cognitive ability) but rather measure views of intelligence, levels of perseverance and knowledge about how one learns, included the constructs of mindset, grit and metacognitive awareness. Regarding the malleability of intelligence the participants, in all levels of mathematics classes at this rural Midwestern University, in this study held the view that intelligence can grow ($M = 4.40$). Interestingly, this finding runs counter to previously published findings by Dweck (2008) which indicated that in

terms mathematics, students have more of a fixed mindset view. On Duckworth's Grit scale, where means range from 1 (not gritty) to 5 (persevere and sustain passion towards a goal), the participants in the current study had an above average self-reported level of grit ($M = 3.40$). This finding may bode well for this young freshmen cohort of students, since research indicates grit levels increase with age (Duckworth & Quinn, 2009).

Lastly, the entire participant total metacognitive awareness of their learning, including the knowledge of and regulation of their learning, was garnered from the 52-item five-point likert-type Metacognitive Awareness Inventory (MAI). Selecting below "3", the middle choice on an item indicates less awareness, and above "3", more awareness. Therefore an individual selecting all "3's" indicates an average awareness. Mean scores on the MAI are thus, as follows: Knowledge of Cognition ($M = 51.0$), Regulation of Cognition ($M = 105.0$), and total MAI is the sum of the two subcomponents ($M = 156.0$). The averages on all three measures of metacognitive awareness for the participants in the current study were as follows: knowledge of cognition ($M = 63.1$), regulation of cognition ($M = 120.3$), and total MAI ($M = 183.4$), which are higher than the means on the inventory, indicating this group of students had a better than average awareness, knowledge, and regulation of their learning.

Discussion on the Differences in Characteristics among Students in Three Levels of Math

Participants in the current study were either in a full-time remediated mathematics class (Elementary or Intermediate Algebra), a part-time remediated mathematics class (Co-requisite College Algebra), or college level class (College Algebra through Calculus I) that had no mathematics remediation component. The percentage of participants in

each group was as follows: 31.4% were in a full-time mathematics remediation course, 16.4% in the part-time co-requisite algebra course, and the remaining 52.2% were not in a mathematics class that required mathematics remediation. With the level and content of mathematics being different between the three categories of classes, the student characteristics within these segregated groups are likely different. The second research question aimed to determine those differences among the students, based on the type of mathematics class they were enrolled in. A discussion of key differences found between the demographic, cognitive, and non-cognitive characteristics among the three groups of students follows.

Key Demographic Differences. One notable finding regarding the demographic traits of the participants enrolled in three different levels of college mathematics classes (full remediation, part-time, and no remediation) offered at the Midwestern regional university, was not a difference between the groups, but instead a similarity. There were not significantly different percentages of female participants among the three mathematics groups, with rates falling between 72% and 75.3% female. This finding indicates whether a student participant was enrolled in a full-time remediation course, a co-requisite part-time remediation course, or a college-level mathematics course such as college algebra up through calculus, a higher proportion of participants were female, which partly contradicts national statistics. Research suggests there are more mathematically under-prepared female students entering as college freshmen compared to males, which the current study also found, however, related research shows more male students are prepared for college-level mathematics than female, which contradicts the current findings (Hill et al., 2010, Lesik, 2006, NCES, 2012, Nook, 2013). While

research suggests the gender difference in mathematics college-readiness is shrinking, this study shows predominantly more female participants are college-ready than their male counterparts. An additional interesting gender-related finding in the current study was that 61% of the female students reported their mother had some college experience, while less than 45% of their fathers had ever attended any post-secondary institution.

The original six ethnic categories on the participant survey were consolidated down to two: under-represented (African American, Native American, Multi-racial, and Hispanic), and over-represented (Caucasian and Asian American). As a result of this split, there were no significant differences in the racial composition within the three groups of mathematics participants, however, the Asian and White students made up higher percentages of college-level mathematics classes (nearly 60%), while the other minority participants made up higher percentages of remediation classes. A report by Pryor et al. (2006), confirms this current finding by stating racial minority students are “still lagging behind their Asian and White peers with respect to academic preparedness in mathematics upon college entry” (p. 21). Though not statistically analyzed in the current study, percentages of Native Americans seemed eminently different with over 42% of the participants enrolled in a part-time remediated mathematics class, while less than 16% were in a college-level mathematics class. In addition, all Asian participants were in college-level courses.

In this current study all non-traditional participants who were over 25 years of age, were enrolled in either Elementary or Intermediate Algebra, the full-time remediation courses. This percentage, 3.1%, of all participants in the current study, is in accordance with national statistics (NCES, 2010b) that indicate higher rates of non-

traditional students enroll in remediation courses, compared to traditional-aged incoming freshmen.

The last notable finding was that significantly higher percentages of full-time remediation students (72%) reported that their father never went to college (postsecondary vocational schools through 4-year institutions), as compared to part-time and no remediation students, which suggests the father's education is strongly related to college remediation enrollment. A higher rate of participants, whose mothers went to college (63.9%), enrolled in college-level math, though this was not significantly different than the remediation groups. Nelson (2009) suggested parents education is important, for those with college experience are more aware of the many aspects of and benefits from college and can therefore better support their children.

Key Precollege Differences. Prior high school academic achievement, including high school GPA and SAT or ACT standardized test scores, are often viewed as precollege cognitive indicators for future success (Strong American Schools, 2008). In the current study, participants enrolled in college level classes (College Algebra through Calculus I) had significantly higher high school GPA's, ACT Composite and ACT Mathematics scores than students enrolled in either level of remediation (Full- or Part-time). This finding was confirmed by Brown (2012) who determined as high school GPA or SAT scores increase, the need for remediation decreases.

Key Non-cognitive Differences. Participants who had to enroll in a mathematics class with any level of remediation, held similar beliefs as the college level mathematics students, regarding the mindset that intelligence is not fixed, i.e., it is malleable and can grow. Significantly different however, were the levels of grit, knowledge of cognition

and total metacognitive awareness between participants immersed in a fully remediated mathematics course and the participants not requiring any remediation.

This finding on grit is important for it suggests students enrolled in the lowest level of mathematics courses offered at the rural Midwestern University, do not persevere through mathematics challenges, troubles and mistakes or strive towards achieving a long term goal, as well as the students enrolled in credit-bearing, college-level mathematics courses (Duckworth, et al., 2007). Additionally, full remediation students (Elementary and Intermediate Algebra students) in the current study, had significantly lower complete metacognitive awareness, and knowledge of cognition, as compared to the non-remediated students. This finding implies mathematically under-prepared students in full-time remediated mathematics classes have less knowledge of their own academic skills and abilities, including which procedure to use and when to use certain strategies, than the college-ready mathematically academically prepared participants. Fostering metacognitive awareness is important because it affords students the ability to manage skills in order to develop even better skills (Bransford et al., 2000).

Discussion on the Predictors of Academic Achievement

The third research question examined which characteristics (demographic, cognitive, and non-cognitive) of the participants predicted academic success as indicated by final letter grades in their mathematics classes. The participants were divided into two groups: *Any Remediation* included students enrolled in Elementary, Intermediate, or Co-requisite Algebra, and *No Remediation* included those in College Algebra through Calculus I. To determine any differences among these two groups, in terms of characteristics that influence final grades, correlation analyses were conducted first,

followed by regression analyses.

Key Correlations. The findings from this analysis include several key differences among the two groups with respect to the correlations between their final grades and participant characteristics. For the *Any Remediation* group, ethnicity, post-CPT scores, knowledge of cognition, and grit were significantly correlated with their final letter grades. With ethnicity being a dichotomous variable in this study (1 = over-represented, and 0 = under-represented) these results indicate the final grades of White and Asian remedial mathematics participants were higher than the other minority students. There were no precollege cognitive indicators associated with success for students in mathematics remediation. Conversely, high school GPA, and ACT Mathematics score were significantly correlated to final grades for the *No Remediation* group. Thus, those participants in this group with higher precollege indicators than their peers, had higher college mathematics final grades. The higher the independent variable in this case, the higher the outcome. Grit was commonly significantly correlated with this grades for both groups of mathematics students in the current study. Interestingly, though the level of grit between *Any Remediation* and *No Remediation* groups were significantly different, with remediation students having significantly lower mean grit scores than the college-ready students as noted earlier, grit was found to be significantly correlated with grades for both groups. Importantly this suggests participants in this study who self-report as having perseverance and passion towards achieving long term goals, exhibit grit and academically achieve higher grades than those with less grit. Similar findings can be stated with respect to the knowledge of cognition variable. Though significantly lower means for this *Any Remediation* group versus the *No Remediation* group were realized in

this study, participants needing any remediation that had higher knowledge of cognition than their peers, also had higher final grades.

Key Predictors. For the group of students needing mathematics remediation, findings of the regression analyses, determined the significant characteristics that predict academic achievement were ethnicity and grit, which are in line with the correlation analysis noted above. While previous high school academic performance, high school GPA, was a significant predictor of academic achievement for the *No Remediation* group, grit was also a significant predictor for the college-ready mathematics students. Once again this analysis confirms the correlation results.

Discussion on the Predictors of College Retention

The objective of the fourth research question was to determine which characteristics (demographic, cognitive, and non-cognitive) of the remediation student participants predicted their retention, as indicated by participant enrollment the following semester, at the rural Midwestern regional university. To gain a baseline of the retention of mathematics remediation participants, the discussion begins with the retention rates of the entire group of first-time freshmen mathematics remediation participants (90.8%), the full-time remediation participants (88.0%) which is a combined group with both Elementary and Intermediate Algebra participants in it, and the part-time (96.2%) Co-Requisite first-time freshmen participants. Statistically the full and part-time groups were not different, which implies regardless of the level of remediation a student was in, equal percentages of the first-time freshmen returned to the university to begin their second semester. A statewide report (OSHRE, 2015) on first-time freshmen still enrolled one year later, in any postsecondary institution university within the state was 76.6% at

regional universities, which is not an exact comparison, but it does at least shed a positive light on the current retention rates at the research site.

As for the characteristic that predict retention the logistic regression test was run with demographic variables first, then only the pre-collegiate cognitive indicators, and lastly and solely, just the non-cognitive variables. Statistical analysis revealed the demographic composition (gender, ethnicity, and parent's education) of the first-time freshmen mathematics remediation students in this study cannot predict whether this group of students re-enrolled the next semester, post-CPT scores did predict retention, meaning the higher the post-CPT score was, the greater the odds a remediation student would return the nest semester. Total metacognitive awareness was a significant predictor of retention, which suggests the odds a student in a mathematics remediation course returning the next semester, increase as total metacognitive awareness increases.

Implications

The results of this study are relevant to all postsecondary institutions who strive to support and develop the full potential of the diverse freshmen students entering various mathematics classes in college. Determining a multitude of characteristics of the diverse students allowed the current researcher to attain a holistic characterization of first-year freshmen. Dissemination of the summary and analysis of these multiple traits may help other educators alter or develop new mathematics courses to better assist in the knowledge and skill development students need to be successful. This study is a unique in its attempt to provide a demographic, cognitive, and non-cognitive foundational image of first-semester students enrolled in various levels of mathematics classes, and the academic achievement and retention of this diverse group.

Not only do the results of this study have implications for teachers who teach various levels of mathematics to an ever growing diverse group of students entering post-secondary schools, but they also have implications for students in those classrooms. This study informs teachers of the demographics and typical high school success indicators, like high school grade point averages, standardized test scores, or university placement test scores, but it also enlightens both teachers and students about other non-cognitive characteristics like grit, metacognitive awareness, as well as differing views on how intelligence can grow.

First, looking at the demographic composition of the participants, the study found one demographic predictor of academic achievement, no predictors for retention amongst the mathematics remediation participants, however, important finding for two demographic groups were realized, and are important to share. Determining that most students were white and, they achieved higher than any other racial group, and ethnicity predicted academic achievement for mathematics remediation students, was not surprising based on prior research and therefore not very informative. Though ethnicity, nor any other demographic trait considered in this study, predicted retention, national statistics still calculate and report retention rates based on ethnicity, thus the findings here are an important addition to those research entities. It is also important to intimate the findings from this study, that indicate female students can succeed in mathematics, whether enrolled in a remedial course or a college-level course, and in fact, they can out-perform their male counterparts in any level of mathematics. The idea that women can in fact achieve success in mathematics, as shown in the results, should be promoted and emphasized in all mathematics courses on this campus, and nationwide. Lastly, with high

percentages of Native American participants in this study, and with most enrolled in mathematics remediation classes, as compared to any other Non-White ethnicities, it is important to help this population of student to succeed, as research indicates Native Americans struggle with mathematics in school (Orona, 2015) and have the lowest retention and graduation rates amongst ethnicities (NCES, 2009). As result of this set of findings, demographic characteristics of freshmen should continue to be studied.

If this current study only used demographic characteristics to predict achievement and retention, this study would not be very informative. Colleges and universities also use precollege indicators, like high school GPA and ACT scores, to predict academic achievement and retention. This part of the study has implications for teachers and students, as it demonstrates the need to understand past history as it may predict future success. With nearly half the participants in this study enrolled in a mathematics remediation course, teachers and students need to know research indicates the likelihood of these under-prepared students succeeding, is lower than those students not needing remediation. Precollege differences in high school GPA and ACT scores between remediation and non-remediation groups were found, and final grades in their mathematics courses were also significantly different. Precollege indicators did not predict the academic achievement or retention for the remediation students, though GPA predicted the academic success of the college-level mathematics students. With equal percentages of each group passing their course, albeit with different letter grades, it is important to understand these indicators, but they do not alone help explain these results.

Third, this study informs teachers and students about other non-cognitive factors that contribute to the success of first-time freshmen students. Research has indicated the

mindset, level of grit, and the metacognitive awareness students possess, enable students to learn and achieve success (Dweck, 2011; Garcia, 2014; Tough, 2012). The results of this part of the study have implications for the teacher and the student. Though participants had similar views that intelligence can increase (growth mindset) regardless of level of mathematics class they are, Dweck (2008) determined mathematics was more of a fixed mindset subject, i.e., you either can do mathematics or you cannot do math. Mathematics remediation students has significantly lower levels of grit and knowledge of cognition, than the college-level mathematics students. Researchers suggest level of grit can increase, and students can become more knowledgeable of their own learning, thus teachers and students must understand this potential. This important as results indicate mathematics participants in this study, regardless of level of mathematics course, who had higher grit had higher final grades, and higher retention rates. Knowledge of cognition was also a predictor of retention for the remediation students.

With Complete College America promoting the co-requisite model for students needing part-time remediation, understanding various characteristics of freshmen has become important. If teachers can learn more characteristics about their students, and if students can learn new or develop non-cognitive constructs, then perhaps remediation students can succeed as college-level mathematics students have demonstrated.

Recommendations for Future Research

The results of this study revealed differences between first-year freshmen students requiring mathematics remediation, and those in college-level mathematics courses. Demographically the groups were different, coming into college they brought different academic preparedness, non-cognitively there were differences, and the predictors of

success were not similar. Further research is needed on how to help students improve non-cognitive characteristics. Also, while there were many variables considered all at once during this study, groups had to be collapsed to do statistical analyses, and subcomponents within the non-cognitive constructs were not analyzed. As a result the following recommendations for future studies include:

- Additional research is needed to determine if non-cognitive supplemental instruction at the beginning of a semester of mathematics remediation, can increase non-cognitive indicators, and ultimately improve academic achievement and retention as compared to college-level students.
- With a small sample size of full-time and part-time mathematics remediation, studying similar students across the state, or in regional university within the state, may help discover successful trends indicated by their academic achievement.
- Native American students comprised the second largest percentage of participants in the current study, and represent a large proportion of students at the rural Midwestern University, but separate non-cognitive trait analyses was not performed, due to collapsing these students with African American and Hispanic students. With research also indicating less success in mathematics at college for Native Americans, additional research on non-cognitive characteristics and indicators of success should be conducted.
- First-generation students may not have learned how to succeed in college. Parents who went to college can offer their experiences to their children. Studying non-cognitive differences between the groups may result in indicators

for success. Another option is to study the impact of non-cognitive interventions on their achievement.

- Female students made up three-fourths of all participants. Future research on females may include trying to determine if the higher percentage of female students in the current study is attributed to Smith's (2008) notion that there is a higher female participation response to surveys than males, or instead accredited to the mother's college experiences having an influence on their daughters enrollment in college. Additionally, differences in non-cognitive indicators of success and retention was not performed on female students based on level of mathematics class.
- Grit has two subcomponents: perseverance and passion. Metacognitive awareness inventory used in this study, had two as well, knowledge of cognition (K of C) and regulation of cognition (R of C). However, K of C and R of C have subcomponents under each of those. The current study did not include individual analyses of the lowest level subcomponents for each of these instruments. It would be interesting to look deeper into these constructs with this groups of students, since the data is there, or with other populations.

Identifying various characteristics that lead to success, for various groups of students is a research process that needs to continue for all students, but maybe more so for the under-prepared, under-represented, and the unsuccessful remediation students.

Conclusion

Educators need to determine characteristics of diverse freshmen students who do not succeed in their mathematics courses and decide to drop out of college. Conversely,

educators also need to learn the characteristics of successful mathematics students. How might educators increase the academic achievement and retention of diverse first-time freshmen students enrolled in various levels of first-year mathematics courses? Boylan (1999) believes good education begins with “an institutional commitment to the concept of educational development” (p. 4).

To develop students, educators must know more about them. Understanding prior academic achievement and their demographics provides key information, and the non-cognitive beliefs students have, helps complete their picture. Since research has indicated grit, metacognitive awareness and growth mindset views on intelligence play a role in the success of students (Bransford et al., 2000; Duckworth et al., 2007; Dweck et al. 1995; Pintrich, 2002), students should surely become aware of them, and teachers should promote these ideas. With the co-requisite model approach to mathematics being offered at the current university, and institutions across the country, perhaps time can be spent changing their mindsets, and developing their grit and metacognitive awareness, characteristics that predict academic achievement could help students achieve success.

For students who successfully complete a remediation course, the likelihood of re-enrolling increases (Lesik, 2007). Without helping this group succeed, the national trend of remediation students exiting the college completion pipeline, will continue.

REFERENCES

- ACT. (2015). *The Condition of College & Career Readiness 2015*. Retrieved from www.act.org/readiness/2015.
- Arendale, D.R. (2002). Then and now: The early years of developmental education. *Research in Teaching in Developmental Education, 18*(2), 5-23.
- Aronson, J., Fried, C.B., & Good, C. (2002). Reducing the effects of stereotype threat on African American college students by shaping theories of intelligence. *Journal of Experimental Social Psychology, 38*, 113-125.
- Ary, et al. 2010. 2006. *Introduction to Research in Education*. Wadsworth: Cengage Learning.
- Bahr, P. R. (2011), A typology of students' use of the community college. *New Directions for Institutional Research, 2011*(S1), 33–48. doi:10.1002/ir.415
- Bahr, P. (2008). Does mathematics remediation work? A comparative analysis of an academic attainment among community college students. *Research in Higher Education, 49*(5), 420-450. doi: 10.1007/s11162-008-9089-4.
- Bailey, T., Jeong, D. W., & Cho, S.-W. (2010). Referral, enrollment, and completion in developmental education sequences in community colleges. *Economics of Education Review, 29*(2), 255–270.
- Bandura, A. (1997). *Self-efficacy: The exercise of self-control*. New York, NY: W.H. Freeman and Company.

- Bandura, A. (1989). Social cognitive theory. In R. Vasta (Ed.), *Annals of Child Development, (6)*. Six theories of child development, 1 - 60. Greenwich, CT: JAI Press.
- Barnes, W., Slate, J.R., & Rojas-LeBouef, A. (2010). College-readiness and academic preparedness: The same concepts? *Current Issues in Education, 13*(4), 1-28.
- Berkner, L., He, S., & Cataldi, E.F. (2002). *Descriptive summary of 1995–96 beginning postsecondary students: Six years later* (NCES 2003–151). Washington, DC: U.S. Department of Education. National Center for Education Statistics.
- Bernstein, D.A., Penner, P.A, Clarke-Stewart, A., & Roy, E.J. (2006). *Psychology*. Boston: Houghton Mifflin Company
- Bettinger, E., Boatman, A., & Long, B. (2013). Student supports: Developmental education and other academic programs. *The Future of Children: Postsecondary Education in the United States, 23* (1), 93–115.
- Bettinger, E. & Long, B.T. (2008). *Addressing the needs of under-prepared students in higher education: Does college remediation work?* (NBER Working Paper 11325). Cambridge, MA: National Bureau of Economic research. Retrieved from the National Bureau of Economic Research: <http://www.nber.org/papers/w11325>.
- Bettinger, E., & Long, B. T. (2005). Remediation at the community college: Student participation and outcomes. *New Direction for Community Colleges, 129*(1), 17-26.
- Blackwell, LS., Trzesniewski, K.H., & Dweck, C.S. (2007). Implicit theories of intelligence predict academic achievement across adolescent transition: A longitudinal study and an intervention. *Child Development, 78*, 246-263.
- Boaler, J. (2013) Ability and Mathematics: the mindset revolution that is reshaping education. *Forum, 55*(1), 143-152.

- Bol, L., Campbell, K.D., Perez, T., & Yen, C.J. (2015). The effects of self-regulated learning training on community college students' metacognition and achievement in developmental math courses. *Community College Journal of Research and Practice, 40*(6), 480-495. doi:10.1080/10668926.2015.1068718
- Boylan, H.R. (1999). Developmental education: Demographics, outcomes, and activities. *Journal of Developmental Education, 23*(2). Retrieved from <http://www.ncde.edu>
- Bransford, J.D., Brown, A.L., & Cocking, R.R. (2000). *How people learn: Brain, mind, experience, and school*. Washington, D.C.: National Academy Press.
- Brothen, T. & Wambach, C.A. (2004). Refocusing developmental education. *Journal of Developmental Education, 28*(2), 16-33.
- Brown, J. M. (2012). Online Learning: A comparison of web-based and land-based courses. *Quarterly Review of Distance Education, 13*(1), 39-42. AN: 78098502
- Brown, H., D. (1981). Second language learning: Psycholinguistic factors. In R. B. Kaplan (ed). *Annual review of applied linguistics* (pp. 108-123). Rowley, MA: Newbury.
- Burchard, M. S., & Swerdzewski, P. (2009). Learning effectiveness of a strategic learning course. *Journal of College Reading and Learning, 40*(1), 14-34.
- Bureau of Labor Statistics. (2003). Volunteering in the United States, 2003. Retrieved from <https://www.bls.gov/news.release/hsgsec.nr0.htm>.
- Burkley, M., Parker, J., Stermer, P.S., & Burkle, E. (2010). Trait beliefs that make women vulnerable to math disengagement. *Personality and Individual Differences, 48*, 234-238.
- Calcagno, J. C., & Long, B. T. (2008). *The impact of postsecondary remediation using a regression discontinuity approach: Addressing endogenous sorting and noncompliance*. Retrieved from <http://files.eric.ed.gov/fulltext/ED501553.pdf>

- Camara, W.J. (2005). Broadening Predictors of College Success. In W.J. Camara and E.W. Kimmel (Eds.), *Choosing Students: Higher Education Admissions Tools for the 21st Century*, 81–105. Mahwah, NJ: Lawrence Erlbaum Associates.
- Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor analytic studies*. New York: Cambridge University Press.
- Centra, J.A. (1978). College enrollment in the 1980s: Projections and possibilities. *ETS Research report Series*, 1978(2), 1-37. doi: 10.1002/j.2333-8504.1978.tb01165.
- Cermak, K., & J. Filkins. (2004). On-campus employment as a factor of student retention and graduation. Report for Academic Affairs and OIPR, University of DePaul, Chicago.
- Chang, Winnie, "Grit and Academic Performance: Is Being Grittier Better?" (2014). *Open Access Dissertations*. 1306.
http://scholarlyrepository.miami.edu/oa_dissertations/1306
- Chen, I. (2014, July 16), *New research: Students benefit from learning that intelligence is not fixed* [Mindshift]. Retrieved from
<http://blogs.kqed.org/mindshift/2014/07/new-research-students-benefit-from-learning-that-intelligence-is-nit-fixed>.
- Choy, S. (2001). *Students whose parents did not go to college: Postsecondary access, persistence, and attainment. Findings from The Condition of Education 2001 (NCES 2001-126)*. Washington, DC: National Center for Educational Statistics (NCES); U.S. Department of Education.
- Claro, S., Paunesku, D., and Dweck, C. S. (2016). Growth mindset tempers the effects of poverty on academic achievement. *Proc. Natl. Acad. Sci. U.S.A.* 113, 8664–8668. doi: 10.1073/pnas.1608207113.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences (2nd ed.)*. Hillsdale, NJ: Erlbaum.

- Complete College America. (2012, Spring). *Remediation: Higher Education's bridge to nowhere*. Retrieved from <http://completecollege.org/resources/>
- Conley, D.T. (2007). *Redefining college readiness*. Volume 3. Eugene, OR: Educational Policy Center.
- Core-Principles Organization. (2015). *Core principles for transforming remediation within a comprehensive student success strategy: A joint statement*. Retrieved from http://www.core-principles.org/uploads/2/6/4/5/26458024/core_principles_nov9.pdf.
- Crede, M., & Kuncel, N. R. (2008). Study habits, skills, and attitudes: The third pillar supporting collegiate academic performance. *Perspectives on Psychological Science*, 3(6), 425–453.
- Creswell, J. W. (2008). *Educational Research: Planning, Conducting, and Evaluating Quantitative and Qualitative Research*. Upper Saddle River, NJ: Pearson Prentice Hall.
- Cross, D.R., & Paris, S.G. (1988). Development and instructional analysis of children's metacognitive and reading comprehension. *Journal of Educational Psychology*, 30(2), 131-142. doi:10.1037/0022-0663.80.2.131.
- Devers, A. (2015) Thinking about Intelligence: How Student Mindsets Influence Academic Performance. *A Rising TIDE*, 8, 1–23.
- Donovan, M.S.& Bransford, J.D. (2005). How Students Learn: History, Mathematics, and Science in the Classroom (p.1-28). Washington D.C.: The National Academies Press.
- Doyle, B. P. (2013). *Metacognitive awareness: Impact of a metacognitive intervention in a pre-nursing course*. (Doctoral Dissertation, Louisiana State University). Retrieved from http://digitalcommons.lsu.edu/gradschool_dissertations/2644
- Duckworth, A. L., & Eskreis-Winkler, L. (2013). True grit. *Observer*, 26(4), 1-3.

- Duckworth, A.L., & Quinn, P.D. (2009). Development and validation of the Short Grit Scale (GritS). *Journal of Personality Assessment*, *91*, 166-174.
<http://www.sas.upenn.edu/~duckwort/images/Duckworth%20and%20Quinn.pdf>.
doi:10.1080/00223890802634290
- Duckworth, A.L., Peterson, C., Matthews, M.D., & Kelly, D.R. (2007). Grit: Perseverance and passion for long-term goals. *Journal of Personality and Social Psychology*, *9*, 1087-1101. doi:10.1037/0022-3514.92.6.1087
- Duckworth, A. L., & Seligman, M. E. P. (2005). Self-discipline outdoes iq in predicting academic performance of adolescents, *Psychological Science*, *16*, 939–944.
- Dweck, C., Walton, G. M., & Cohen, G. L. (2011). *Academic tenacity: Mindsets and skills that promote long-term learning*. Paper presented at the Gates Foundation, Seattle, WA.
- Dweck, C.S. (2008). Can personality be changed?: The role of beliefs in personality and change. *Directions in Psychological Science* *41*(6), 391-394.
- Dweck, C.S. (2006). *Mindset: The new psychology of success*. New York, NY: Random House.
- Dweck, C. S. (1999). *Self-theories: Their role in motivation, personality, and development*. Philadelphia: Psychology Press.
- Dweck, C., Chiu, C., & Hong, Y. (1995). Implicit theories and their role in judgments and reactions: A world from two perspectives. *Psychological Inquiry*, *6*(4), 267-285.
- Dweck, C.S., & Leggett, E.L. (1988). A social cognitive approach to motivation and personality. *Psychological Review*, *95*, 256–273.

- Easton J. (2013). *Using measurement as leverage between developmental research and educational practice*. Paper presented at the Center for Advanced Study of Teaching and Learning Meeting; Charlottesville, VA. 2013. Paper retrieved from <http://ies.ed.gov/director/pdf/Easton062013.pdf>.
- Everson, H.T., & Tobias, S. (1998). The ability to estimate knowledge and performance in college: A metacognitive analysis. *Instructional Science*, 26, 65–79.
- Flavell, J.H. (1979). Metacognition and cognitive monitoring: A new area of cognitive developmental inquiry. *American Psychologist*, 34, 906-911.
- Furr, S.R. & Elling, T.W. (2000). The influence of work on college student development, *ASPA Journal*, 37(2), 454-470.
- Garcia, E. (2014). *The need to address non-cognitive skills in the education policy agenda*. EPI Briefing Paper #386. Economic Policy Institute. Retrieved from: <http://goo.gl/i3kFV2>
- Gault, B. L., Reichlin, L., Reynolds, E., & Froehner, M. (2014). *4.8 million college students are raising children*. Fact Sheet, IWPR #C424. Washington, DC: Institute for Women’s Policy Research. Retrieved from <http://www.iwpr.org/publications/pubs/4.8-million-college-studentsare-raising-children>.
- Good, C., Aronson, J., & Inzlicht, M. (2003). Improving adolescents’ standardized test performance: An intervention to reduce the effects of stereotype threat. *Journal of Applied Developmental Psychology*, 24, 645 – 662.
- Good, C., Rattan, A., & Dweck, C.S. (2007a). *Theories of intelligence influence females’ sense of belonging, intent to continue, and achievement in math*. Unpublished data, Columbia University, 2007.
- Gorman, R. (2015). *An examination of academic grit in urban high schools* (Doctoral dissertation). Retrieved from <http://scholarworks.wmich.edu/dissertations/1174>.

- Gutman, L. M., & Schoon, I. (2013). *The impact of non-cognitive skills on the outcomes of young people. Literature review*. London, UK: Education Endowment Foundation. Retrieved from https://educationendowmentfoundation.org.uk/uploads/pdf/Non-cognitive_skills_literature_review_1.pdf
- Hammann, L. A., & Stevens, R. J. (1998) Metacognitive awareness assessment in self-regulated learning and performance measures in an educational psychology course. (ERIC Document Reproduction Service No. ED 424249).
- Heckman, J. J., and Y. Rubinstein. (2001). The importance of noncognitive skills: Lessons from the ged testing program, *American Economic Review* 91(2), 145–149.
- Henderson, V. L., & Dweck, C. S. (1990). Achievement and motivation in adolescence: A new model and data. In S. Feldman & G. Elliott (Eds.) *At the threshold: The developing adolescent*. Cambridge, MA: Harvard University Press.
- Hesser, T. L. (2015). *The impact of embedded support for underprepared students in a college chemistry course*. Retrieved from <https://search.proquest.com/docview/1681371179?accountid=12831>
- Higbee, J.L. & Thomas, P.V. (1999). Affective and cognitive factors related to mathematics achievement. *Journal of developmental Education*, 23(1), 8-24.
- Hill, C., Corbett, C., & St. Rose, A. (2010). *Why so few? Women in science, technology, engineering, and mathematics*. Washington DC: American Association for University Women.
- Hogan, M.L. (2013). *Non-cognitive traits that impact female success in big law*. (Unpublished doctoral dissertation). University of Pennsylvania.
- Horn, L., & Nevill, S. (2006). *Profile of undergraduates in U.S. postsecondary education institutions: 2003–04, with a special analysis of community college students* (No. 2006-184). Washington, D.C.: U.S. Department of Education, National Center for Education Statistics.

- Hoyt, J.E., & Sorenson, C.T. (2001) High school preparation, placement testing, and college remediation. *Journal of Developmental Education*, 25(2), 26-34 (2001).
- Jones, B. D., Byrd, C. N., & Lusk, D. (2009). High school students' beliefs about intelligence. *Research In The Schools*,16(2), 1-14.
- Kamphaus, R. W. (2001). *Clinical assessment of child and adolescent intelligence*. Needham Heights, MA: Allyn and Bacon.
- Keith, T.Z. (2006). *Multiple regression and beyond*. Boston: Pearson Education.
- Kemp, A. (2014, September 2). Many oklahoma students start college taking remedial classes. *The Oklahoman*. Retrieved from <http://newsok.com/many-oklahoma-students-start-college-taking-remedial-classes/article/5337902>
- Kuh, G.D., Kinzie, J., Schuh, J.H., & Whitt, E.J. (2005). *Student success in college: Creating conditions that matter*. San Fancisco, CA: Jossey-Bass.
- Leech, N, Barrett, K, & Morgan, G. A. (2011). *IBM SPSS for intermediate statistics (4th ed.)*. New York, NY: Routledge.
- Lesik, S. A. (2006). Applying the regression discontinuity design to infer causality with non-random assignment. *The Review of Higher Education*, 30(1), 1-19.
- Lewis, H.R. (1997). Harvard University Mission Statement. Retrieved January 4, 2015 from <http://www.harvard.edu/faqs/mission-statement>.
- Lomax, R,G., & Hahs-Vaughn, D.L. (2012). *Statistical concepts: A second course (4th ed.)*. New York: Taylor & Francis Group.
- Long, T.L. (2014, June). *Addressing the academic barriers to higher education*. The Brookings Institution. Retrieved from http://www.hamiltonproject.org/papers/by_topic/education.
- Long, B. T. (Ed.) (2003) Who can afford college? The economics behind access. *Cambridge: Harvard Graduate School of Education*.

- Long, B.T., & Boatman, A. (2013). The role of remediation and developmental courses in access and persistence. In *The State of College Access and Completion: Improving College Success for Students from Underrepresented Groups*, edited by Anthony Jones and Laura Perna, 77–95. New York: Routledge Books.
- Martinez, M. E. (2006). What is metacognition? *Phi Delta Kappan*, 696-699.
- Mattern, K. D., Shaw, E. J., & Marini, J. (2013). *Does college readiness translate to college completion?* (College Board Research Report No. 2013-9). New York, NY: The College Board.
- McCabe, R.H. (2000). *No one to waste: A report to public decision makers and community college leaders*. Washington, DC: Community College Press.
- McPheron, B. (2016). Ohio State University Mission Statement. Retrieved Fall 2016 from <https://oaa.osu.edu/vision-mission-values-goals.html>.
- Memnun, D.S. (2013). A comparison of metacognitive awareness levels of future elementary teachers in Turkey and USA. *Educational research and Reviews*, 8(6), 277-288.
- Memnun, D.S. & Hart, L.C. (2012). Elementary school mathematics teacher trainees' metacognitive awareness levels: Turkey case. *Journal of International Education Research*, 8(2), 173-182.
- Mitchell, J. (2014, November, 17). Remedial courses in college stir questions over cost, effectiveness. *The Wall Street Journal*. Retrieved from <http://www.wjs.com>.
- Mindset. (n.d.) in Merriam Webster's online directory (11th ed.) Retrieved from <http://m-w.com/dictionary/mindset>.
- Mokhtari, K., Reichard, C. (2002). Assessing students' metacognitive awareness of reading strategies. *Journal of Educational Psychology*, 94(2), 249-259.
doi:10.1037/0022-0663.94.2.249

- Murphy, L., & Thomas, L. (2008). *Dangers of a Fixed Mindset: Implications of Self-Theories Research for CS Education*. In Proceedings of the 13th Annual Conference on Innovation and Technology in Computer Science Education, Madrid, Spain, June-July 2008. Retrieved from <http://db.grinnell.edu/sigcse/iticse2008/Program/viewAcceptedProposal.asp?sessionType=paper&sessionNumber=12>.
- Mytkowicz, P., Goss, D., & Steinberg, B. (2014). Assessing metacognition as a learning outcome in a postsecondary strategic learning course. *Journal of Postsecondary Education and Disability*, 27(1), 51 – 62.
- Narode, R. (1989). *A Constructivist program for college remedial mathematics at the university of massachusetts, amherst*. Retrieved from ERIC database. (ED309988).
- National Center for Education Statistics. (2015). *The Condition of Education*. (NCES Report 2015-144). Retrieved from <https://nces.ed.gov/pubs2014/2014015.pdf>.
- National Center for Education Statistics. (2012). *Postsecondary Education enrollment*. Retrieved from <https://nces.ed.gov/pubs2014/2014015.pdf>.
- National Center for Education Statistics. (2012). *Postsecondary Education Enrollment*. Retrieved from <https://nces.ed.gov/pubs2011/2011015.pdf>.
- National Center for Education Statistics. (2009). Table 151: Percentage of public and private high school graduates taking selected mathematics and science courses in high school, by sex and race/ethnicity: Selected years, 1982 through 2005. In U.S. Department of Education, National Center for Education Statistics (Ed.), *Digest of Education Statistics* (2009 ed.). Retrieved from http://nces.ed.gov/programs/digest/d09/tables/dt09_151.asp.
- National Center for Public Policy and Higher Education. (2010). *Beyond the rhetoric: Improving college readiness through coherent state policy*. Retrieved from www.highereducation.org/reports/reports.shtml.

- National Center for Public Policy and Higher Education. (2010b). *Nontraditional students*. Retrieved from <http://nces.ed.gov/programs/coe/2002/analyses/nontraditional/sa01.asp>.
- National Council of Teachers of Mathematics (NCTM). *Principles and Standards for School Mathematics*. Reston, VA: NCTM, 2000.
- Nelson, J.K. (2009). Impact of Parent Education on Student Success. *Online Submission*. Retrieved from <http://ehis.ebscohost.com/eds/detail?sid=06414799-4d46-40e6-a9bd-1d4d6d36052c%40sessionmgr114&vid=1&hid=116&bdata=JnNpdGU9ZWRzLWxpdmU%3d#db=eric&AN=ED507263>
- Nook, M.A. (2013). University of Wisconsin System: Remedial Education Report. Retrieved from <https://www.wisconsin.edu/developmental-remedial-education/download/FINAL%20Internal%20Remedial%20Education%20report>.
- Oklahoma State Regents for Higher Education. (February, 2008). *Annual student remediation report*. Retrieved from <http://okhighered.org/studies-reports/remediation>.
- Oklahoma State Regents for Higher Education. (February, 2013). *Participation in developmental education for oklahoma high school graduates in oklahoma public higher education*. Retrieved from <http://www.okhighered.org/studies-reports/preparation/RemediationRates.shtml>.
- Oklahoma State Regents for Higher Education. (February, 2013). *Comparison of developmental and non-developmental education student success in college algebra by cohort years 2000-01 to 2007-08*. Retrieved from <http://www.okhighered.org/studies-reports/preparation/RemediationRates.shtml>.

- Orona, C. (2013) *Efficacy and utility beliefs of mothers and children as predictors of mathematics achievement for american indian students* (Doctoral dissertation). Retrieved from https://shareok.org/bitstream/handle/11244/11031/Orona_okstate_0664D_12920.pdf?sequence=1
- Panaoura, A., & Philippou, G. (2003). *The construct validity of an inventory for the measurement of young pupils' metacognitive abilities in mathematics*. In N.A. Pateman, B. J. Doherty & J. Zilliox (Eds.). *Proceedings of the 27th Conference of the International Group for the Psychology of Mathematics Education* (pp. 437-444), Honolulu, HI: PME.
- Paris, S.G., & Winograd, P. (1990). How metacognition can promote academic learning and instruction. In B.J. Jones & L. Idol (Eds.), *Dimensions of thinking and cognitive instruction* (pp. 15-51). Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.
- Pascarella, E. T., & Terenzini, P. T. (2005). *How college affects students, Vol.2: A third decade of research*. San Francisco, CA: Jossey-Bass.
- Perkins-Gough, D. (2013). The Significance of grit: A conversation with Angela Lee Duckworth *Educational Leadership*, 71(1), 14-20. Retrieved from <http://www.ascd.org/publications/educational-leadership/sept13/vol71/num01/The-Significance-of-Grit@-A-Conversation-with-Angela-Lee-Duckworth.aspx>
- Pintrich, P. R., (2002). The role of metacognitive knowledge in learning, teaching, and assessing. *Theory Into Practice*, 41(4), 219-225.
- Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, 82, 33-40.

- Pryor, J.H., Hurtado, S., Saenz, V.B., Korn, J.S., Santos, J.L., & Korn, W.S. (2006). *The American Freshman: National Norms for Fall 2006*. Los Angeles: Higher Education Research Institute, UCLA.
- Pucheu, P. M. (2008). *An investigation of the relationships between the scoring rubrics inventory and the metacognitive awareness inventory as reported by secondary school core-subject teachers* (Doctoral dissertation). Available from ProQuest Dissertations & Theses Full Text. (89145269). Retrieved from <http://search.proquest.com/docview/89145269?accountid=12725>
- Reed, J. F. (2015). *Influence of metacognitive awareness on motivation and performance in high school precalculus*. Retrieved from <https://search.proquest.com/docview/1772400727?accountid=12831>.
- Renfro, S., & Armour-Garb, A. (1999). *Open admissions and remedial education at the City University of New York*. New York: Mayor's Advisory Task Force on the City University of New York.
- RinconGallardo, T. J. (2009). *The effect of the use of learning journals on the development of metacognition in undergraduate students*. (Doctoral dissertation). Retrieved from <https://search.proquest.com/docview/305244621>.
- Robins, R. W. & Pals, J. L. (2002). Implicit self-theories in the academic domain: Implications for goal orientation, attributions, affect and self-esteem change. *Self and Identity, 1*, 313-336.
- Robinson, W. (2015) *Grit and demographic characteristics associated with nursing student course engagement* (Doctoral dissertation). Retrieved from <https://scholarworks.iupui.edu/>
- Roderick, M., Nagaoka, J., & Coca, V. (2009). College readiness: The challenge for urban high schools. *The Future of Children, 19*(1), 185-210. doi: 10.1353/foc.0.0024

- Rojas, J. P., Reser, J. A., Usher, E. L., & Toland, M. D. (2012). Psychometric properties of the academic grit scale. Lexington: University of Kentucky.
- SAS.com (n.d.) Giving you the power to know since 1976. Retrieved from https://www.sas.com/en_us/company-information.html.
- Schmidt, P. (2008). 3 new studies question the value of remedial college courses. *The Chronicle of Higher Education*, 54(43), A18. Available from <http://chronicle.com/article/3-New-Studies-Question-the/7005>.
- Schonberger, A. (1985). *Developmental Mathematics in College: What the Research Is and Why There Isn't More*. Retrieved from ERIC database. (ED256439).
- Schraw, G., Crippen, K., & Hartley, K. (2006). Promoting self-regulation in science education: Metacognition as part of a broader perspective on learning. *Research in Science Education*, 36, 111-139. doi: 10.1007/s11165-005-3917-8.
- Schraw, G. (1998). Promoting general metacognitive awareness. *Instructional Science*, 26(1-2), 113-125.
- Schraw, G., & Dennison, R.S. (1994). Metacognitive theories. *Educational Psychological Review*, 74(4), 173-208. doi: 10.1007/BF02212307.
- Smith, M.J. (2013). An exploration of metacognition and its effect on mathematical performance in differential equations. *Journal of the Scholarship of Teaching and Learning*, 13(1), 100-111.
- Smith, G. (2008). Does gender influence online survey participation?: A record-linkage analysis of university faculty online survey response behavior. *ERIC Document Reproduction Service No. ED 501717*.
- Snyder, M. (1993). Basic research and practical problems: The promise of a “functional” personality and social psychology. *Personality and Social Psychology Bulletin*, 19, 251–264.

- Sperling, R.A., Howard, B.C., Miller, L.A., & Murphy, C. (2002) Measures of children's knowledge and regulation of cognition. *Contemporary Educational Psychology* 27, 51–79. doi: 10.1006/ceps.2001.1091.
- Sriram, R. (2014). Rethinking intelligence: The role of mindset in promoting success for academically high-risk students. *Journal of College Student Retention: Research, Theory & Practice*, 15(4), 515-536. doi:10.2190/CS.15.4.c.
- Strayhorn, T. L. (2013). What role does grit play in the academic success of Black male collegians at predominantly White institutions? *Journal of African American Studies*, 18(1), 1–10. doi:10.1007/s12111-012-9243-0.
- Strong American Schools. (2008). Diploma to nowhere. Retrieved from <http://www.deltacostproject.org/resources/pdf/DiplomaToNowhere.pdf>
- Stump, G., Husman, J., Chung, W-T., & Done, A. (2009). *Student Beliefs About Intelligence: Relationship to Learning*. Paper presented at the Frontiers in Education Conference, San Antonio, TX, October 2009. Retrieved from <http://fie-conference.org/fie2009/papers/1283.pdf>.
- Teo, T., & Lee, C. (2012). Assessing the factorial validity of the metacognitive awareness inventory (MAI) in an Asian country : A confirmatory factor analysis. *International Journal of Educational and Psychological Assessment*, 10(2), 92-103.
- Tessema, M., Ready, K., & Astani, M. (2014). Does part-time job affect college students' satisfaction and academic performance (GPA)? The case of a mid-sized public university. *International Journal of Business Administration*, 5 (2), 50-59.
- Thomas, G.P., & McRobbie, C.J. (2001). Using a metaphor for learning to improve students' metacognition in the chemistry classroom. *Journal of Research in Science Teaching*, 38(2), 222–259.

- Titus, M.A. (2004). An examination of the influence of institutional content on student persistence at four-year colleges and universities: A multilevel approach. *Research in Higher Education*, 45 (7): 673– 699.
- Tough, P. (2012). *How children succeed: Grit, curiosity, and the hidden power of character*. New York: Houghton Mifflin Harcourt .
- Vandal, R. (2013). *Scaling co-requisite: Spanning the divide*. Retrieved from www.completecollegeamerica.org.
- Veenman, M. V. J., Kok, R., & Blöte, A. W. (2005). The relation between intellectual and metacognitive skills in early adolescence. *Instructional Science*, 33, 193-211.
- Venezia, A., & Jaeger, L. (2013). Transitions from high school to college. *The Future of Children*, 23 (1), 117-136.
- Wenz, M., & Yu, W. (2010). Term-time employment and the academic performance of undergraduates *Journal of Education Finance*, 35(4), 358-373.
- Witkow, M.R., Huynh, V., & Fuligni, A.J. (2015). Understanding differences in college persistence: A longitudinal examination of financial circumstances, family obligations, and discrimination in an ethnically diverse sample. *Applied Developmental Science*, 19(1), 4-18. doi: 10.1080/10888691.2014.946030.
- Young, A., & Fry, J.D. (2008). Metacognitive awareness and academic achievement in college students. *Journal of the Scholarship of Teaching and Learning*, 8 (2), 1-10.

APPENDIX A

INSTITUTIONAL REVIEW BOARD APPROVAL FROM NORTHEASTERN STATE UNIVERSITY

IRB 17-039 Approval

Institutional Review Board Nov 21

Human Subjects Review

Proposal Title: Academic Abilities and Non-Cognitive Traits of College Remedial Mathematics Students
IRB # 17-039

Dear Mr. Kruczek and Dr. Uoley

Your research proposal has been approved by the Institutional Review Board at Northeastern State University. It is the IRB's opinion that you have provided adequate safeguards for the welfare of the participants in this study.

You are authorized to begin your research and implement this study as of the start date listed in your application, or the date of this communication if you listed the start date as "As soon as possible," "Upon IRB Approval," or a similar phrase. This authorization is valid until the end date listed in your application, or for one year after approval of your study, whichever is earlier. You may request an extension of up to one year, provided the request is made before the approval period ends. For student research as part of a course, approval ends when the course ends unless the instructor/faculty sponsor notifies IRB in writing that supervision will continue, or if another faculty sponsor notifies IRB of assuming supervision responsibilities.

This approval is granted with the understanding that the research will be conducted within the published guidelines of the NSU Institutional Review Board and as described in the approved version of the application (attached). Any changes or modifications to the approved protocols should be submitted to the IRB for approval if they could substantially affect the safety, rights, and welfare of the participants in your study. Please use the IRB number in all your communications.

Thank you for sending us your application for research involving human subjects. By doing so, you safeguard the welfare of participants in your study and federal funding of our university.

Sincerely,

Jim Carroll
Chair, Institutional Review Board
Northeastern State University

APPENDIX C
ADULT CONSENT FORM

PROJECT TITLE:

Academic Abilities and Non-cognitive Traits of First-time Freshmen College Remedial Mathematics Students

INVESTIGATOR:

Karl Kruczek, Doctoral Student, Oklahoma State University
Juliana Utley, Ph.D., Oklahoma State University

PURPOSE:

The purpose of this survey-design quantitative study is to first understand whom the students are that come to post-secondary institutions underprepared for college-level mathematics coursework, and then determine which variables are predictors of academic success and retention. The researcher will investigate the demographic characteristics, mindsets, levels of grit, metacognitive knowledge, academic performance, and retention rates of college-level and remedial math students at Northeastern State University.

PROCEDURES:

You will complete an online questionnaire. This questionnaire includes a demographic information, a grit scale (Grit-S), an Implicit Theory of Intelligence (Mindset) scale and a Metacognitive Awareness Inventory (MAI). The demographic survey will ask you to state your: age, gender, race/ethnicity, facts about your last math class, study habits, goals and person(s) influencing your decision to attend college/career. The other surveys ask questions about your perseverance with math, your beliefs about whether intelligence can grow or is fixed, and your awareness of how you think and how you regulate your thinking. This questionnaire will take approximately 20 to 30 minutes. At the end of the questionnaire, you will be asked whether you wish to participate in a drawing for one of three gifts. The drawings are for an Amazon Fire tablet, a \$100 VISA gift card, and a \$100 Walmart gift card.

Your name and Student ID are necessary to have initially on the questionnaire in order to match other data such as your Final letter grade in Math, High School GPA, etc. Once all data has been collected your name and student ID will be replaced with a code such as FA16-001, FA16-002, etc.

RISKS OF PARTICIPATION:

There are no known risks associated with this project which are greater than those ordinarily encountered in daily life.

BENEFITS OF PARTICIPATION:

We expect these research results to inform our understanding about the characteristics first-time freshmen students bring to Northeastern State University math classes. If you are interested, a copy of the results can be sent to you at the conclusion of the study.

CONFIDENTIALITY:

All information will be kept in a secure place that is open only to the researchers. This information will be saved as long as it is scientifically useful; typically, such information is kept for five years after publication of the results. Results from this study may be presented at professional meetings or in publications. You will not be identified individually. Note that Qualtrics has specific privacy policies of their own. If you have concerns, you should contact this service directly. Qualtrics' privacy statement is provided at <http://qualtrics.com/privacy-statement>.

COMPENSATION:

Participants who complete all questionnaires and surveys will be entered in a drawing for one of three gifts: An Amazon Fire Tablet, a \$100 VISA gift card, and a \$100 Walmart gift card.

CONTACTS:

You may contact the researcher at the following addresses and phone numbers, should you desire to discuss your participation in the study and/or request information about the results of the study:

Karl Kruczek
Oklahoma State University Doctoral Student
Northeastern State University Mathematics Instructor
232 Science Building
Tahlequah, OK 74464
Office: (918)444-3031
kruczek@nsuok.edu
karl.kruczek@okstate.edu

or

Dr. Juliana Utley, Ph.D.
Interim Associate Dean for Research, Engagement and Graduate Studies
Associate Professor, Mathematics Education
Morsani Chair in Mathematics, Science, and Technology Education
Director, Center for Research on STEM Teaching and Learning
332 Willard Hall, Oklahoma State University
Stillwater, OK 74078
405-744-7476
juliana.utley@okstate.edu

If you have questions about your rights as a research volunteer, you may contact:

Oklahoma State University Institutional Review Board
219 Cordell North
Stillwater, OK 74078
405-744-3377
irb@okstate.edu

PARTICIPANT RIGHTS:

I understand that my participation is voluntary, that there is no penalty for refusal to participate, and that I am free to withdraw my consent and participation in this project at any time, without penalty.

CONSENT DOCUMENTATION:

If you choose to participate: Please, click NEXT if you choose to participate. By clicking NEXT, you are indicating that you freely and voluntarily agree to participate in this study and you also acknowledge that you are at least 18 years of age.

APPENDIX D

UNDERGRADUATE MATH STUDENT DEMOGRAPHIC SURVEY

Are you a First semester freshmen: Yes No

Name: _____ **University ID Number:** _____

Age: _____ **Gender:** Male Female No Response

Select the ethnicities that you consider yourself:

White African American Native American Asian American

Hispanic Other

Marital Status: Single Married Separated Divorced

Number of children living with you full time: 0 1 2 3 More than 3

Number of children living with you part time: 0 1 2 3 More than 3

Highest grade level competed by your mother (or female guardian):

Bachelor's degree or higher

Some college (including vocational or technical) but did not finish

High School Diploma G.E.D. Did not graduate High School

Does Not Apply

Highest grade level competed by your father (or male guardian):

Bachelor's degree or higher

Some college (including vocational or technical) but did not finish

High School Diploma G.E.D. Did not graduate High School

Does Not Apply

Select the math course you are in, while completing this survey:

Elementary Algebra Intermediate Algebra College Algebra with Lab

College Algebra Applied Math Statistics Trigonometry

Calculus I Discrete Math Intro to Proof

Do you have a job? (Circle one) Yes No

If yes, is it: On Campus Off Campus Both

How many total hours per week do you work? _____

APPENDIX E

IMPLICIT THEORY OF INTELLIGENCE

Read each sentence below and circle the one that shows how much you agree with it.

THERE ARE NO RIGHT OR WRONG ANSWERS.

- 1. You have a certain amount of intelligence, and you really can't do much to change it.**

1	2	3	4	5	6
Strongly	Agree	Mostly	Mostly	Disagree	Strongly
Agree		Agree	Disagree		Disagree

- 2. Your intelligence is something about you that you can't change very much.**

1	2	3	4	5	6
Strongly	Agree	Mostly	Mostly	Disagree	Strongly
Agree		Agree	Disagree		Disagree

- 3. You can learn new things, but you can't really change you basic intelligence.**

1	2	3	4	5	6
Strongly	Agree	Mostly	Mostly	Disagree	Strongly
Agree		Agree	Disagree		Disagree

- 4. No matter who you are, you can change your intelligence a lot.**

1	2	3	4	5	6
Strongly	Agree	Mostly	Mostly	Disagree	Strongly
Agree		Agree	Disagree		Disagree

- 5. You can always greatly change how intelligent you are.**

1	2	3	4	5	6
Strongly	Agree	Mostly	Mostly	Disagree	Strongly
Agree		Agree	Disagree		Disagree

6. No matter how much intelligence you have, you can always change it quite a bit.

1
Strongly
Agree

2
Agree

3
Mostly
Agree

4
Mostly
Disagree

5
Disagree

6
Strongly
Disagree

APPENDIX F

GRIT SCALE

Read each sentence below and then circle the one that shows how much you agree with t.

THERE ARE NO RIGHT OR WRONG ANSWERS.

- 1. New mathematical ideas and concepts sometimes distract me from previous ones.**

- | | | |
|---------------------------------|-----------------------|------------------------|
| 1. Very much like me
like me | 2. Mostly like me | 3. Somewhat
like me |
| 4. Not much like me | 5. Not like me at all | |

- 2. When solving mathematical problems, setbacks (delays and obstacles) do not discourage me. I bounce back from disappointments faster than most people.**

- | | | |
|---------------------------------|-----------------------|------------------------|
| 1. Very much like me
like me | 2. Mostly like me | 3. Somewhat
like me |
| 4. Not much like me | 5. Not like me at all | |

- 3. I have been obsessed with a certain mathematics idea for a short time but later lost interest.**

- | | | |
|---------------------------------|-----------------------|------------------------|
| 1. Very much like me
like me | 2. Mostly like me | 3. Somewhat
like me |
| 4. Not much like me | 5. Not like me at all | |

- 4. In mathematics, I am a hard worker.**

- | | | |
|---------------------------------|-----------------------|------------------------|
| 2. Very much like me
like me | 2. Mostly like me | 3. Somewhat
like me |
| 5. Not much like me | 5. Not like me at all | |

5. **In mathematics, I often set a goal but later choose to pursue (follow) a different one.**

- | | | |
|---------------------------------|-----------------------|-------------|
| 1. Very much like me
like me | 2. Mostly like me | 3. Somewhat |
| 4. Not much like me | 5. Not like me at all | |

6. **I have difficulty maintaining (keeping) my focus on math concepts that take more than a few months to complete.**

- | | | |
|---------------------------------|-----------------------|-------------|
| 1. Very much like me
like me | 2. Mostly like me | 3. Somewhat |
| 4. Not much like me | 5. Not like me at all | |

7. **I finish whatever I begin in mathematics.**

- | | | |
|---------------------------------|-----------------------|-------------|
| 1. Very much like me
like me | 2. Mostly like me | 3. Somewhat |
| 4. Not much like me | 5. Not like me at all | |

8. **I am diligent (hardworking and careful) with my mathematics.**

- | | | |
|---------------------------------|-----------------------|-------------|
| 1. Very much like me
like me | 2. Mostly like me | 3. Somewhat |
| 4. Not much like me | 5. Not like me at all | |

APPENDIX G

METACOGNITIVE AWARENESS INVENTORY

The following questions ask about the strategies you use when approaching your coursework.

Remember there are no right or wrong answers, just answer as accurately as possible.

Use the scale below to answer the questions. If you think the statement is very true or you indicate 5; if a statement is not at all true of you, indicate 1. If the statement is more or less true of you, find the number between 1 and 5 that best describes you.

1	2	3	4	5
Not at all true of me		Neutral		Very true of me

1. I ask myself periodically if I am meeting my goals:
2. I consider several alternatives to a problem before I answer
3. I try to use strategies that have worked in the past.
4. I pace myself while learning in order to have enough time.
5. I understand my intellectual strengths and weaknesses.
6. I think about what I really need to learn before I begin a task.
7. I know how well I did once I finish a test.
8. I set specific goals before I begin a task.
9. I slow down when I encounter important information.
10. I know what kind of information is most important to learn.
11. I ask myself if I have considered all options when solving a problem.
12. I am good at organizing information.
13. I consciously focus my attention on important information.
14. I have a specific purpose for each strategy I use.
15. I learn best when I know something about the topic.
16. I know what the teacher expects me to learn.
17. I am good at remembering information.
18. I use different learning strategies depending on the situation.
19. I ask myself if there was an easier way to do things after I finish a task.
20. I have control over how well I learn.
21. I periodically review to help me understand important relationships.

22. I ask myself questions about the material before I begin.
23. I think of several ways to solve a problem and choose the best one.
24. I summarize what I've learned after I finish.
25. I ask others for help when I don't understand something.
26. I can motivate myself to learn when I need to.
27. I am aware of what strategies I use when I study.
28. I find myself analyzing the usefulness of strategies while I study.
29. I use my intellectual strengths to compensate for my weaknesses.
30. I focus on the meaning and significance of new information.
31. I create my own examples to make information more meaningful.
32. I am a good judge of how well I understand something.
33. I find myself learning helpful strategies automatically.
34. I find myself pausing regularly to check my comprehension.
35. I know when each strategy I use will be most effective.
36. I ask myself how well I accomplished my goals once I'm finished.
37. I draw picture or diagrams to help me understand while learning.
38. I ask myself if I have considered all options after I solve a problem.
39. I try to translate new information into my own words.
40. I change strategies when I fail to understand.
41. I use the organizational structure of the text to help me learn.
42. I read instruction carefully before I begin a task.
43. I ask myself if what I'm reading is relation to what I already know.
44. I reevaluate my assumptions when I get confused.
45. I organize my time to best accomplish my goals.
46. I learn more when I'm interested in the topic.
47. I try to break studying down into smaller steps.
48. I focus on overall meaning rather than specifics.
49. I ask myself questions about how well I am doing while I am learning something new.
50. I ask myself if I learned as much as I could have once I finish a task.
51. I stop and go back over new information what is not clear.
52. I stop and reread when I get confused.

VITA

Karl Michael Kruczek

Candidate for the Degree of

Doctor of Philosophy

Thesis: ACADEMIC ABILITIES AND NONCOGNITIVE TRAITS OF FIRST-TIME FRESHMEN: COLLEGE-LEVEL & REMEDIAL MATHEMATICS STUDENTS

Major Field: Professional Studies: Mathematics Education

Biographical:

Education:

Completed the requirements for the Doctor of Philosophy in your Professional Studies: Mathematics Education at Oklahoma State University, Stillwater, Oklahoma in July in 2017.

Completed the requirements for the Master of Mathematics Education at Northeastern State University, Tahlequah, OK in 2009.

Completed the requirements for the Bachelor of Science in Biomedical Engineering at University of Bridgeport, Bridgeport, CT in 1987.

Experience:

2009 to present Mathematics Instructor, Northeastern State University, Tahlequah, OK

1997 to 2009 Lecturer of Mathematics, Northeastern State University, Tahlequah, OK

1987-1995 Radar Systems test Engineer, Northrop-Grumman Norderm Systems, Norwalk, CT

Professional Memberships:

Research Council of Mathematics Learning
National Council of Teachers of Mathematics