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The Role of Academic Achievement Motivation in Predicting Performance on the Northwest Evaluation Association's Measure of Academic Progress. Mindsets: Incremental vs. Entity Beliefs About Intelligence

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M.A., Counseling and Educational Psychology, New Mexico State University, 2010

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DISSERTATION

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To my wife Emily for her enduring love and support, my daughters, Cadence and Aria, for their patience with the time dad spent “writing his book”, and to my mother, Carol D‘Antonio, for instilling in me a never ending curiosity and passion for learning.

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Abstract

A cross-sectional correlational study was conducted in order to evaluate the relationship between a student's mindset (incremental vs. entity beliefs about intelligence) and their score on the Northwest Evaluation Assessment (NWEA) Measure of Academic Progress (MAP) in the areas of Math, Reading, and Language. The NWEA MAP is a computer adaptive test aligned with the Common Core Standards. Students' mindsets were measured using Dweck's (2000) *Implicit Theories of Intelligence Scale for Children*.

The study was conducted at a college preparatory charter school in a metropolitan area of the Southwestern United States. Participants included 307 middle school students in grades 6-8. Question predictor and control variables were evaluated through descriptive statistics and estimated bivariate correlation matrices. Nested taxonomies of multiple regression models for each of the NWEA MAP subject tests were constructed. The control variables evaluated include: gender, ethnicity, race, socioeconomic status,

special education participation, gifted education participation, grade point average, attendance, and year in school.

Results indicated that there was a small to moderate, statistically significant estimated correlation between student mindset and NWEA MAP performance across all subject tests. Contingent on the subject test, specific control predictors were identified as mediating this relationship. There were negative estimated correlations found between the NWEA MAP subject tests and ethnicity (math), socioeconomic status (math and reading), and special education (reading and language). There were positive estimated correlations found between GPA and gifted program identification across math, reading, and language subject tests. In support of previous findings suggesting student mindset is associated with student achievement, this study provides further evidence that student mindset correlates with student performance on standardized tests and that this estimated correlation is mediated by subgroup factors.

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Chapter I: Introduction

Non-cognitive psychological constructs have received increased attention in the research effort seeking to identify effective and efficient strategies to increase student achievement and close the achievement gap (Gutman & Schoon, 2013). This shift has pushed researchers in education and psychology to look beyond psychometrically measured cognitive traits and observable behaviors to an evaluation of the underlying psychological processes that drive them. Emotional and motivational constructs are increasingly being explored in an effort to comprehensively evaluate why some students find academic success despite setbacks or negative circumstances whereas others do not (Holmlund & Silva, 2009; Miller, 2013; Seligman, 2012). Of these constructs, Carol Dweck's (2006) mindset theory has received increased consideration due to its strong theoretical foundation and the significant empirical evidence that has been collected in support of this theory (Blackwell, Trzesniewski, & Dweck, 2007; Paunesku, 2013; Paunesku et al. (2015); Romero, Paunesku, & Dweck, 2011; Yeager & Walton 2011; Yeager, Walton, & Cohen, 2013).

Current research into mindset theory focuses on the role of mindset interventions in increasing academic achievement (Yeager, Paunesku, Walton, & Dweck, 2013). However, significant gaps in the mindset literature remain when evaluating the role of mindset in standardized test performance. Given the current K-12 educational reform emphasis on standardized test performance in the United States, which was amplified by the passing of No Child Left Behind (Bush, 2001), and the evidence in support of mindset interventions, there is a relative dearth of research addressing the role mindset plays in student performance on standardized tests. Furthermore, while mindset research has provided insight into the role subgroup factors (i.e. race, ethnicity, socioeconomic

status) play in the ability to use mindset as a predictor of student academic achievement, limited research has directly assessed the role these factors play in mediating mindset's ability to predict performance on standardized tests.

Rationale for the Study

The rationale for this study was to evaluate the role of mindset in the performance of students on the Northwest Evaluation Association (NWEA) Measure of Academic Progress (MAP) standardized test. The use of high stakes standardized tests in education to evaluate students, teachers, schools, and govern graduation and college acceptance have been on the rise (Amrein & Berliner, 2002), and the manipulability of individual mindsets and the resulting achievement gains have been established (Blackwell et al., 2007; Yeager, Paunesku, et al., 2013). These interventions have proven to be cost effective and can be deployed on a large scale (Paunesku, 2013; Yeager, Paunesku, et al., 2013). Despite mounting evidence highlighting the importance of mindset in achievement, there is limited research evaluating the relationship between mindset and achievement on standardized tests. By examining the predictive value of mindset in standardized test performance, students and educators can better prioritize the role of motivational interventions in an effort to increase performance on standardized tests.

Current research indicates that those that may benefit the most from mindset intervention are those who have found the least success in the educational system, specifically individuals of lower socioeconomic status (SES) and minority students (Aronson, Fried, & Good, 2002; Blackwell et al., 2007; Good, Aronson, & Inzlicht, 2003). If mindset is identified as an effective intervention in improving the scores of these students, it could contribute significantly to closing the standardized test

achievement gap. Additionally, since non-cognitive skills have been identified as predictors of numerous major life accomplishments (Rosen, Glennie, Dalton, Lennon, & Bozick, 2010), evidence for the role of mindset in increasing standardized test performance could encourage public schools to allocate additional funds for targeting the development of mindset and other non-cognitive skills.

Theoretical Framework for the Study

Dweck and colleagues' work on mindset theory in many ways parallels the trends and developments of the field of psychology dating back to the middle of the 20th century. Over the last 60 years, the evolution of psychological theory has been described as a progression from behaviorism, to cognitivism, to post-cognitivism (Potter, 2000). Mindset theory helps to bridge the boundaries between these theoretical distinctions by drawing from and contributing to each theoretical perspective (Higgins, Kruglanski, & Lange, 2012).

Dweck describes her early work as drawing heavily on Orval Mowrer's (1960) pioneering research into hopelessness, Seligman and Maier's (1967) work studies exploring the idea of learned helplessness, and Bernard Weiner's (1985) attribution theory. Dweck also credits Kelly's (1955) theory of personality and Heider's (1958) theory of social perception as theoretical antecedents to her early work on what would eventually develop into mindset theory. The foundation for mindset theory was established when Dweck and Leggett (1988) proposed a motivational model articulating goal theory. This model not only sought to identify and describe behavior but also addressed the underlying psychological processes that drove the behaviors.

Finally, mindset theory draws from the theoretical and empirical debate regarding the understanding of intelligence. Dweck has characterized this debate as a dichotomy between entity (fixed) vs. incremental (malleable) views of intelligence. Theorists who defended intelligence as a fixed trait-like *Bell Curve* include Herrnstein and Murray (1996). However, Dweck is a firm incrementalist in agreement with psychologist Alfred Binet (1909/1973), sociologist Benjamin Bloom (1985), paleontologist Steven Gould (1981), and creativity researcher John Hayes (1989), and cites research by neuroscientists in support of her view on malleable intelligence (Dweck, 2006; Doidge, 2007). Mindset theory represents an important nexus across time and fields of research, providing powerful insights into motivation, how it can be influenced, and the resulting impact on student achievement.

Statement of the Problem

The primary problem addressed by this study is the lack of research that has been conducted directly evaluating the relationship between mindset and standardized test performance. The secondary problem this study sought to examine is the role that subgroup factors play in the ability of mindset to predict performance on standardized tests.

Research Question

The primary research question examined in the current study assessed the relationship between mindset (entity vs. incremental beliefs) and student performance on the Northwest Evaluation Association's (NWEA) Measure of Academic Progress (MAP). The relationship between subgroup factors (demographics, academic programs, and academic achievement measure by GPA, attendance, and year in school) and mindset's

ability to predict student performance on the NWEA MAP was also of interest in the current study.

Definition of Terms

Mindset Theory. According to Dweck (2006), mindset theory states that people fundamentally view the world from fixed or growth perspectives. Those with a growth mindset believe that basic skills and qualities can be formed through effort, strategy application, and accessing help from others. These individuals see intelligence as a flexible trait and tend to have more learning or mastery-oriented goals and will more frequently persist in the face of difficulty or failure. A fixed mindset perspective views individuals as unchangeable and endowed with an immutable amount of intelligence. Fixed mindset individuals tend to have more performance-oriented goals and tend to not persist in the face of failure or difficulty. It is estimated that approximately 40% of individuals are fixed minded, 40% are growth minded, and 20% are of mixed mindset (Dweck, 2006). Mindset theory has also been referred to as implicit theories of intelligence (Dweck, Chiu, & Hong, 1995).

Growth Mindset (incremental beliefs about intelligence). According to Dweck (2006) this is a view that intelligence is a malleable trait that can be expanded through effort, strategy application, and accessing the help of others. Growth minded individuals are more likely to persist in the face of challenge or failure and have learning or mastery goal orientations. Growth mindedness is synonymous with incremental beliefs about intelligence (Dweck et al., 1995).

Fixed Mindset (fixed beliefs about intelligence). According to Dweck (2006), those with a fixed mindset view intelligence as a fixed trait and are less likely to attribute failure to effort or strategy selection. Fixed minded individuals are less likely to persist

in failure and tend to be more performance oriented in their goals. Fixed mind set is synonymous with entity beliefs about intelligence (Dweck et al., 1995).

Northwest Evlauation Association Measure of Academic Progress (NWEAMAP). The NWEA MAP is a computer adaptive test (CAT) based on the U.S. Common Core standards. The assessment is normed on students from across all 50 states in the U.S. and is commonly used in K-12 education as a short cycle assessment administered each fall, winter, and spring in order to track student proficiency and growth on curriculum objectives (NWEA, 2004).

Chapter II: Literature Review

Current research has moved beyond cold cognitive learning models in attempts to quantify non-cognitive traits that influence academic achievement (Shell, Brooks, Trainin, Wilson, Kauffman, & Herr, 2010). Examples of non-cognitive academic traits or skills include self-efficacy, self-regulated learning, and motivation (Rosen, Glennie, Dalton, Lennon, & Bozick, 2010). Research using mindset theory offers considerable empirical evidence and clarity for researchers, practitioners, and students. The theory offers a motivational model that describes clear patterns of behavior and achievement, as well as the underlying psychological processes that drive them (Dweck and Legget, 1988). More importantly, effective, scalable interventions that improve academic achievement have been deployed across many educational settings and significant empirical evidence has been collected documenting successful intervention (Blackwell et al., 2007; Paunesku, 2013; Yeager & Walton 2011).

Mindset theory has emerged as a leading area of focus in the study of motivation across primary, secondary, and tertiary educational settings (Yeager, Walton, et al., 2013). This research suggests that those with a growth mindset view of intelligence are more likely to apply more effort and persist in the face of failure by viewing setbacks as related to effort and strategy selection as opposed to those with fixed mindset views of intelligence who attribute failure and success to immutable or fixed levels of intelligence (Dweck, 2006).

Current research in this area is largely focused on the effectiveness of growth mindset interventions on the academic achievement of students (Blackwell et al., 2007; Romero, Paunesku, & Dweck, 2011; Yeager & Dweck, 2012). While findings suggest

there is sufficient evidence to warrant growth mindset interventions, additional research is necessary in order to understand the impact of mindset on subgroup outcomes and across different measures of academic achievement. Specifically, insufficient information is available regarding the role demographic or academic program factors such as gender, SES or giftedness play in mindset's ability to predict academic achievement. The growing importance of measuring academic achievement by performance on standardized tests demonstrates the need to evaluate the role academic achievement motivation plays in student performance on these assessments. This study was designed to contribute to answering these questions.

Intelligence and the Malleability of Intelligence

The concept of neuroplasticity, which has had a significant impact on mindset theory, has established that brains are capable of improvements and growth throughout the life span (Doidge, 2007). This has fundamentally altered science's understanding of how the brain works, and, subsequently the understanding of the nature of intelligence. Despite these findings, misconceptions regarding intelligence persist.

The contemporary psychological and educational concept of intelligence is rooted in the general intelligence factor *g* first articulated by Charles Spearman (1904) and measured by Alford Binet (1909/1973). With this common definition of intelligence came a new tool for scientific evaluation of the old debate regarding the role of heredity on intelligence as compared to environmental influences (nature vs. nurture). Mainstream twentieth century research promoted the dominant role of heritability in intelligence. The dominance of this heritability view was challenged by the late 1970's. Major contributors to this challenge of the dominance of heritability included Hans

Jürgen Eysenck (1977), Arthur Jensen (1978) and Stephen J. Gould (1981). These researchers challenged the methodology of perhaps the most influential researcher of the heritably of intelligence, Cyril Burt (Jensen, 1978). Despite this effective challenge to the dominance of hereditability as the definer of intelligence, fixed intelligence views in the field of psychology and education persisted. One publication that continued to perpetuate the misconceptions that students were beholden to their predetermined genetic allocation of intelligence was *The Bell Curve* (Herrnstein & Murray, 1996). This attempt to reestablish the dominant role of heredity was effectively challenged again by Gould (1996) and Neisser et al. (1996). They identified significant methodological errors in the studies that had concluded with an emphasis on heritability. A comprehensive summary of the current research on this topic can be found in Nisbett's (2009) book, *Intelligence and How We Get It*. Despite sound scientific evidence challenging the dominance of the heritability of intelligence theory, popular misconceptions persisted.

It has taken advances in medical and research science for the malleability of intelligence to be widely accepted in the scientific and research communities (Doidge, 2007). Advances in neuroscience and neuroimaging in the early 21st century have highlighted the important role that the environment plays in the development of intelligence and the ability of individuals to alter the structures and functions of the brain at any age (Doidge, 2007). According to Nisbett (2009), researchers now see an almost coequal role for environment and heredity in the development of intelligence. Dweck (Higgins, Kruglanski, & Lange, 2012) cites the above debate as contributing significantly to her research and the establishment of the mindset theory, which was built on the premise that intelligence is a malleable trait. With the malleability of intelligence

established, the role of non-cognitive factors such as motivation have become progressively more important, resulting in increased attention by researchers.

Mindset Theory and Academic Achievement: Stages of Theoretical Development

Mindset as a theory of intelligence and a motivational construct is the culmination of three decades of Carol Dweck's research and writing in the field. From learned helplessness to goal orientation to implicit theories of intelligence and interventions, Dweck has provided empirical evidence in the emerging arena of motivational constructs and their measurement. By tracing the development of mindset theory back to its origins, the validity and evidence in support of the theory and its measures has been wellestablished. Through a better understanding of the current interventions being used to leverage Dweck's theory (Blackwell et al., 2007) and the efforts to scale up growth mindset interventions (Paunesku et al., 2015; Yeager, Walton et al., 2013), mindset theory can move into the mainstream of education and to the forefront of the popular understanding of intelligence.

This literature review establishes the context and supports the use of mindset theory in this study. The review of the mindset stages of development seeks to answer two questions posed by Dweck and her fellow researchers. First, why do some individuals persist and eventually succeed despite failures and obstacles while others of similar ability do not? Second, how can interventions be designed to promote persistence in the face of failure and overall increased academic achievement?

The empirical evidence that has been collected in support of Dweck's theory has established the mindset as one of the dominant constructs in motivational research (Renaud-Dubé, Guay, Talbot, Taylor, & Koestner, 2015) Most importantly, Dweck and

others have demonstrated that the growth mindset and resulting academic achievement gains can be attained through practical and affordable interventions (Paunesku et al., 2015). In order to establish a common understanding of mindset theory, it is important to operationalize a definition. In an interview, Carol Dweck defined mindsets in the following way:

> "In a fixed mindset students believe their basic abilities, their intelligence, their talents, are just fixed traits. They have a certain amount and that's that, and then their goal becomes to look smart all the time and never look dumb. In a growth mindset students understand that their talents and abilities can be developed through effort, good teaching and persistence. They don't necessarily think everyone's the same or anyone can be Einstein, but they believe everyone can get smarter if they work at it". (Morehead, 2012)

In order to understand mindset and the constructs the theory represents, Dweck and colleagues' previous works will be evaluated through the lens of stages of theoretical development.

This literature review proposes theoretical stages of the development of mindset theory. These stages will be proposed and reviewed chronologically. A review of the role of seminal quantitative studies from each stage is included. In order to more coherently represent the planned review, the stages of theoretical development are represented in Table 1.

Table 1

Mindset: Stages of Theoretical Development and Significance

Stages	Significance
Stage 1: Learned Helplessness, Attribution Theory, and Goal Orientation	Stage one connected and integrated mastery and helplessness orientation drawing heavily on Weiner's attribution theory (1972, 1985). Diener and Dweck(1978) articulated the divergent responses to failure based on goal orientation; helpless vs. mastery
Stage 2: Underlying Theories of Intelligence: A Motivational Model. Goal orientation as a predictor of academic achievement.	Stage two took the findings of stage one a step further by developing a motivational model connecting learning behavior to goal orientation as predicted by theories of intelligence (Dweck & Legget, 1988). Theories of intelligence are presented as the underlying psychological processes driving goal orientation and behavior (Dweck & Leggett, 1988, Elliot & Dweck 1988).
Stage 3: Mindset Measurement. Development of the *Theories of Intelligence Scale*.	Stage three was defined by an attempt to empirically test the model presented by Dweck and Leggett (1988) by developing an instrument (Dweck et al., 1995; Erdley & Dweck 1993; Henderson & Dweck, 1990) The publication of the *Theories of Intelligence Scale* allowed for a consistent instrument to be used in studying incremental vs. entity beliefs (Dweck, 2000).
Stage 4*:* From Measurement to Intervention. Mindset theory as an educational intervention to improve achievement.	Stage four was defined by experimental manipulation of individual's mindsets and an evaluation of the resulting impact on academic performance. Blackwell et al. (2007) seminal longitudinal study measured, manipulated, and tracked the impact of mindset on student achievement. Large scale follow-up studies supported targeting mindset as a cost effective intervention to increase student performance (Paunesku, 2013; Yeager & Walton, 2011).

These stages are defined by seminal works, which have been influential in the development of mindset theory. Additional works by Dweck and a range of works from other authors are incorporated in development of these themes and in extension of them for each stage of theoretical development. Note that the term mindset did not enter circulation until after Dweck (2006) published her book aimed at popular audiences,

Mindset: The New Psychology of Success: How we can learn to fulfill our potential. However, the term will be used consistently throughout this study for the sake of clarity.

Stage 1: Learned Helplessness, Attribution Theory, and Goal Orientation

Dweck (2000) describes her early research inspiration as arising from a fascination with individuals who accomplished amazing feats, despite facing significant challenges. In this first stage of growth mindset theoretical development, Dweck combines work that was being done in three areas: learned helplessness, attribution theory, and goal orientation. At this stage, Dweck combined the theoretical and empirical work of others with her own research as she sought to establish her own pathway to answering her research question: *Why do some of us persist in the face of failure or challenge while others do not, despite equivalent ability levels?*

Bernard Weiner's (1972) investigation of attribution theory laid the groundwork for Dweck's research into learned helplessness (Dweck, 2000). Inspired by Weiner's research and the work of others, Dweck went on to investigate how learned helplessness could be alleviated. The origins of Dweck's growth mindset can be traced back to her early research into adaptive and maladaptive reactions to failure (Diener & Dweck1978; 1980; Dweck & Reppucci, 1973). According to Dweck, her research on learned helplessness built on the work of Mowrer (1960) and Seligman and Maier (1967). Dweck explained that those she identified as "helpless" were less likely to persist in failure, less likely to take personal responsibility, and were more likely to attribute failure to ability rather than effort (Dweck, 1975). The "helpless" label would eventually morph into the entity theory of intelligence and the "mastery orientation" would become the early label for the incremental theory of intelligence and learning goals. By 2006, Dweck would refer to these orientations as fixed and growth mindsets.

Diener and Dweck (1978) conducted a study to analyze both mastery oriented and helpless students' responses to failure. They described the mastery oriented student failure attribution responses as; "lack of effort" or "increased difficulty of the task" whereas the helpless students emphasized ability as the reason for their lack of success. These and other studies were later combined in a model by Dweck and Leggett (1988) in an attempt to represent the behaviors they were observing and the resulting achievement patterns.

In the search to identify why some persevere in the face of failure and others do not, Dweck saw Bernard Weiner's attribution theory as an important theoretical construct. Weiner's (1985) seminal work "An Attributional Theory of Achievement Motivation and Emotion" clearly influenced Dweck's development of the growth mindset. Weiner explained that his work was derived from the dichotomous explanation of the causal structure of the attribution approach explained by Fritz Heider. Heider wrote, "In common-sense psychology (as in scientific psychology) the results of an action is felt to depend on two sets of conditions, namely, factors within the person and factors within the environment" (Heider, 1958, p.82). Weiner's attribution theory states that success and failure perceptions share three common properties: locus, stability, and controllability with the perceived expectancy resulting in motivational conditions and behaviors (Weiner, 1985). In essence, an individual's perception of locus, stability, and controllability guides behavior and impacts achievement. This theory was clearly integrated into Dweck's growth mindset in which individuals either see their intelligence as stable and out of their control or malleable and under their control. Weiner's work on attributions played a key

role in Dweck making the connection between learned helplessness, goal orientation, behavior, and achievement (Dweck, 2000).

Dweck's most important work in this stage focused on how students responded to failure. Specifically, when and why did some subjects display a "helpless" response while others displayed a "mastery" response and the resulting corresponding performances. Dweck and Reppucci (1973) found that "mastery" subjects responded with persistence in the face of failure while the "helpless" participants responded by more frequently giving up. These participants took less responsibility when compared to the "mastery" participants and when they did take responsibility they focused less on effort (emphasized by the "mastery" participants) and more on ability (Dweck & Reppucci, 1973). Dweck (1975) next sought to evaluate to what degree participants' failure attributions could be manipulated and to what degree this would alter "helpless" participants' responses to failure. Dweck found that in fact participants' attributions in the face of failure could be manipulated and that these manipulations resulted in improved performance (Dweck, 1975). There are clear parallels between this study and the 2007 study conducted by Blackwell et al. Dweck next sought to better understand the performance differences between "helpless" and "mastery" oriented participants. The most important findings from this study foreshadow the fixed vs. entity beliefs Dweck would later incorporate into her theories of intelligence. Specifically, Dweck found that "helpless" students focused on the reasons for failure (lack of ability) while mastery oriented participants focused on how to correct the failure (Diener & Dweck, 1978).

In conclusion, Dweck's early research was heavily influenced by the work done in the areas of learned helplessness, goal orientation, and attribution theory. In terms of

the growth mindset, this stage of theoretical development defines the problem. In stage one, Dweck and fellow researchers identify the two main orientations and their related behavior patterns as "helpless" and "mastery" orientation. These two goal orientations would later be known as learning and performance goals. In stage two, these orientations and related behavior patterns are linked to goal orientations and ultimately theories of intelligence.

Stage 2: Underlying Theories of Intelligence, A Motivational Model: Goal Orientation as a Predictor of Academic Achievement

After having clearly defined the problem in stage one, Dweck now began to answer the questions posed at the start of her research. *Why do some of us persist in the face of failure or challenge while others do not, despite equivalent ability levels?* The answer comes in part by identifying learning vs. performance goals, the theories of intelligence beliefs, and correlating the resulting behaviors. By connecting behavior patterns to underlying psychological processes, Dweck moved from defining the problem to a testable hypothesis.

Stage two is succinctly described by Dweck and Leggett (1988) in the social cognitive model of motivation and personality they developed. In this model, Dweck and Legget describe a three component interrelated model. First, individuals have developed adaptive or maladaptive patterns of behavior (mastery-oriented vs. helpless). Second, these patterns follow directly from individual goal orientation (learning vs. performance goals). Third, Dweck and Leggett propose that these goal orientations are derived from an underlying psychological process related to an individual's implicit theory of intelligence. These implicit theories are described by Dweck and Leggett (1988) as incremental vs. entity theories of intelligence. Those with incremental theories of

intelligence view intelligence as malleable while those with entity theories see intelligence as fixed. This breakthrough clearly lays the groundwork for what Dweck would later popularize as the growth mindset.

Dweck and Leggett (1988) go on to describe the research of mastery orientation (learning goals) and helpless orientations (performance goals) as adaptive and maladaptive respectively. They sought to identify a model that would map out the underlying psychological processes in an attempt to explain how these processes promoted different goal patterns and resulting behaviors. Although Dweck and others had explored goal orientation prior to the development of this model, it was in this model that Dweck formally introduced the now wide spread goal dichotomy of learning goals vs. performance goals. Table 2 describes the relationships of the constructs up to this point:

Table 2

Dweck and Leggett's Model Adapted

Initial orientation constructs as described by Dweck (1978)	Mastery Orientation	Helpless Orientation
Theory of Intelligence	Incremental (Intelligence is Malleable)	Entity (Intelligence is Fixed)
Goal Orientation	Learning Goals (Goal is to increase competence)	Performance Goals (Goal is to gain positive judgment/avoid negative judgment of competence)

Note: Adapted from Leggett, E. L. (1985). Children's entity and incremental theories of intelligence: Relationships to achievement behavior.

Elliot and Dweck (1988) went on to test this model with 5th grade students. The study sought to collect evidence in support of the connection between goal orientation, patterns of behavior, and resulting achievement. To this end, Elliot and Dweck experimentally manipulated goal orientation (learning vs. performance) and the participants' perception

of ability. Elliot and Dweck then went on to measure their task choice, persistence during difficulty, and their verbalizations during difficulty. The model tested in this study is outlined in Table 3.

Table 3

Summary of Goals and Predicted Achievement Patterns

		Predicted Achievement Pattern	
Goal Value	Confidence (perceived level of ability)	Task choice	Response to Difficulty
Performance goal highlighted	High	Sacrifice learning and choose moderate or moderately difficult task to display competence	Mastery-orientation of effective problem solving
	Low	Sacrifice learning and choose moderately easy task to avoid display of incompetence	Learned-helpless response of deterioration in problem-solving and negative overall response
Learning goal highlighted	High or low	Choose learning at risk of displaying mistakes to increase competence	Mastery-orientation of effective problem solving

Note: Adapted from Elliott, E. S., & Dweck, C. S. (1988). Goals: an approach to motivation and achievement. *Journal of Personality and Social Psychology, 54*(1), 5.

The study conducted by Elliot and Dweck (1988) resulted in evidence supporting the model in Table 3. For example, students who had their goal values experimentally manipulated through ability level feedback followed the predicted achievement patterns. Thus, Dweck and fellow researchers had proposed a motivational model and collected evidence in support of that model.

It is important to note here that at this stage of the development Dweck began articulating the generalizability of her theory. For example, Dweck and Leggett (1988)

reviewed the role of entity vs. incremental beliefs in the areas of personality. While the development of this topic is outside of the scope of this review, it is important to note that Dweck has collected convincing empirical evidence to support the application of theories of intelligence (growth mindset) to theories of personality (fixed vs. flexible personality traits and resulting behaviors). Furthermore, Dweck's research continues to address both domains in parallel through her contemporary work.

In summary, stage two marks an important stage in the development of the growth mindset. Dweck and fellow researchers established a testable motivational model integrating the observed behavior patterns of "helpless" and "mastery" oriented children with corresponding goal orientations (performance vs. learning). Finally, Dweck and colleagues described their theoretical hypotheses of the underlying psychological process driving these goal orientations and resulting behavior patterns. Theories of intelligence (entity vs. incremental) are identified as the root psychological process, which would in time form the foundation of Dweck's theory of the growth mindset. In order to empirically evaluate the model Dweck and Leggett proposed, the development of a valid and reliable instrument would be essential. This brings us to the measurement stage of Dweck's development of the growth mindset **Stage 3: Measurement of Theories of Intelligence**

Once Dweck and Leggett proposed their influential motivational model, the next step was to develop an instrument to measure it. The first attempts to measure Dweck and Leggett's (1988) model took place in the early1990s (Erdley & Dweck 1993; Henderson & Dweck 1990,). However, the first comprehensive attempt to measure implicit theories came with the collaboration between Dweck, Chiu and Hong in 1995.

Dweck and colleagues developed a number of related scales that measured an individual's view of traits as malleable or fixed. These scales would later be published by Dweck (2000) in her seminal book, *Self-Theories: Their Role in Motivation, Personality, and Development*. These scales include one domain general scale and a number of domain specific scales. The domain general scale seeks to measure an individual's view on how much individuals can change in general *("Kind of Person" Implicit Theory Form*). Domain specific scales include theories of personality, theories of morality, theories of the world, and theories of intelligence. While both domain general and domain specific scales have amassed compelling validity and reliability evidence, those not related to intelligence are beyond the scope of this study except where they are used to provide supportive validity and reliability evidence for the theory of intelligence measures. This section will specifically review Dweck's (2000) *Theory of Intelligence Scale for Children-Self Form*. This scale is referred to in the rest of this document as *Theory of Intelligence Scale* or ITISCS. First, the measure itself will be described. Next, early stage validity and reliability evidence are presented.

Since Dweck's publication of her scales in 2000, they have been deployed in a wide variety of settings and have been adapted for specific research projects. The scale that will be evaluated here first is the *Implicit Theory of Intelligence* scale (Dweck, 2000). It is important to note that in addition to the validity and reliability evidence supporting the use of these measures, the results have consistently supported theories of intelligence as an independent construct uncorrelated with other constructs and measures (Dweck et al., 1995; Levy, Stroessner, & Dweck 1998). Dweck emphasizes that these scales support her theory that implicit theories of intelligence represent assumptions about one's

self that have cognitive, emotional, motivational, and behavioral consequence but that the *Theory of Intelligence Scale* does not correlate with measures of those traits (Dweck, 2000).

The *Theory of Intelligence Scale* as first investigated in depth by Dweck et al. (1995) consisted of 3 items. The researchers were comfortable with the limited number of items because they viewed implicit theories as a simple unitary theme. Despite the fact that internal reliability of a measure typically increases with the number of questions, the researchers wanted to avoid repetition and disinterest in the scale and were confident in their ability to measure participants' implicit theories with the limited number of items. The items of the implicit theory of intelligence scale include the following; (a) "You have a certain amount of intelligence and you really can't do much to change it," (b) "Your intelligence is something about you that you can't change very much," and (c) "You can learn new things, but you can't really change your basic intelligence." Participant responses were measured on a 6 point Likert scale from 1 (*strongly agree*) to 6 (*strongly disagree*). The scores on each of the 3 items were then averaged to arrive at a composite score ranging from 1 to 6. The higher the score, the more incremental the orientation of the participants' theory of intelligence. In order to ensure that participants were clearly identified as incremental or entity theorists, those with averaged scores greater than 3 and less than 4 were excluded. Participants scoring a 4 or above were identified as incremental theorists while those with averaged scores of 3 or below were identified as entity theorists. Only 15% of the participants were left uncategorized because of averaged scores greater than 3 and less than 4. The remaining 85% were evenly distributed between incremental and entity orientations.

The measure demonstrated significant reliability evidence. Cronbach's alpha internal reliability scores for implicit theories of intelligence scale ranged from .94 to .98. Other domain specific and the domain general scales demonstrated similar reliability. Furthermore, the test retest reliability with a 2-week interval was .80 for the intelligence theory measure. Thus, Dweck et al. (1995) documented considerable reliability evidence across five separate studies including a total of 638 participant (U.S. college students), each of which yielded similar reliability evidence. Much of Dweck and colleague's subsequent work with this measure was built on the validity and reliability evidence collected in this seminal 1995 study but include the evaluation of other populations.

Table 4

Summary Statistics and Reliability of the Implicit Theories of Intelligence Scale

	Mean score	SD	Internal Reliability
Study 1 (N=69)	3.96	1.34	.96
Retest (N=62) (2 week test-retest, r=.80)	3.71	1.39	.98
Study 2 (N=184)	3.80	1.32	.94
Study 3 (N=139)	3.79	1.28	.94
Study 4 (N=121)	3.97	1.13	.96
Study 5 (N=93)	3.73	1.40	.96
Study 6 (N=32)	3.57	1.49	.97

Note: Adapted from: Dweck, et al., (1995). Implicit theories and their role in judgments and reactions: A word from two perspectives. *Psychological inquiry, 6*(4), 267-285.

In addition to the reliability evidence amassed in these studies, considerable validity evidence was collected, building on the strong theoretical frameworks outlined in the previous stages. Stage one of the theoretical development of the growth mindset established the research question, *why do some persist and succeed in the face of failure while others do not*. Stage two, proposed a theoretical hypothesis in response to that question. The collection of validity evidence based on test content, response process,

internal structure, relationship to other variables, and the collection of reliability evidence for instruments to empirically study the theoretical model characterize stage three.

Content validity evidence was clearly laid out in Dweck and Leggett's model (1998). In summary, Dweck and Leggett's model hypothesizes a causal relationship between theories of intelligence (entity vs. incremental), goal orientation (learning vs. performance), and resulting behaviors (attributional response). Based on previous research, they identified theories of intelligence as the underlying psychological process driving goal orientation and the resulting attributional response behaviors. These theoretical findings can be divided into two stages: a) learned helplessness, attribution theory, and goal orientation and b) underlying theories of intelligence. Dweck and colleagues established the link between learned helplessness responses, attribution and goal orientation (Diener & Dweck, 1978, 1980; Dweck, 1975; Dweck & Reppucci, 1973). In this stage, Dweck built on the work of prominent researchers in the field including Bernard Weiner's (1972) Attribution Theory, work done by Mowrer (1960) and Seligman and Maier (1967) regarding learned helplessness, Nicholls (1975) work in the area of effort attributions role in avoiding learned helplessness, and Dweck's (Dweck, 1986; Elliot & Dweck, 1988) conceptualization of learning versus performance goals. The second stage of theoretical development explored the underlying psychological processes that drove individuals to opposing goal orientations and resulting behavior. Dweck and fellow researchers identified the underlying process driving goal selection as incremental and entity theories of intelligence (Dweck & Leggett, 1988, Elliot & Dweck, 1988). Those who believed intelligence was malleable versus those who believed intelligence was a fixed trait responded to failure in different ways. Those who viewed intelligence as

malleable cited strategy and effort as reasons for failure and were less likely to choose a challenging task in subsequent activities while entity theorists more frequently cited lack of ability and chose less difficult tasks (Dweck & Leggett, 1988; Elliot & Dweck 1988).

Response process evidence was collected in support of valid and accurate assessment of participants' theories of intelligence through what today would be a called mixed methods research designs. In a study conducted by Henderson (1990), respondents were asked to explain their answers on the implicit theory of intelligence measure. These respondents' answers were then analyzed and coded. Responses supported the results of the instrument. For example, when participants were asked to explain the reasoning behind their response, those who did not agree with an entity statement would provide justifications clearly aligned to the incremental theory. Furthermore, in a study conducted by Elliot and Dweck (1988) participants were asked to allocate the importance of effort and ability in success along with their completion of theories of intelligence measures using percentages. Participants consistently allocated effort and ability in alignment with their results on the implicit theories of intelligence measure. Those whose results identified them as incremental theorists consistently allocated a higher percentage to effort while those identified as entity theorists more consistently allocated percentages toward ability.

Dweck et al. (1995) presented clear validity evidence based on internal structure of the theories of intelligence measure. Factor analysis was conducted on three separate scales, including theories of intelligence, theories of morality, and theories of the world. Theses scales were represented as separate factors across each of the five studies (see Table 5). As the table shows, the response to each of the questions in the theory of

intelligence scale (F1) correlate with one another to a high degree across all five studies. Similar correlations were found for theories of morality (F2) and theories of the world (F3). Thus, high factor loading across studies provided persuasive evidence that the 3 items in the theories of intelligence scale represent one factor and that they are unique from the other factors assessed by the morality and world theories scales.

Table 5

Factor Analyses of the Implicit Theory of Intelligence Measure

	Factor Loadings														
	Study 1			Study 2			Study 3			Study 4			Study 5		
Items	**F1**	F3	F2	F1	F3	F2	F1	F2	F3	F1	F2	F3	F1	F2	F3
1. You have a certain amount of intelligence and you really can't do much to change it.	**95**	12	17	**94**	13	12	**94**	13	12	**96**	4	16	**96**	7	9
2. Your intelligence is something about you that you can't change very much.	**94**	20	13	**95**	12	7	**96**	15	10	**95**	6	15	**94**	13	15
3. You can learn new things, but you can't really change your basic intelligence.	**93**	13	16	**91**	5	13	**91**	7	12	**93**	6	14	**95**	11	15

Note: Adapted from: Dweck et al., (1995). Implicit theories and their role in judgments and reactions: A word from two perspectives. *Psychological inquiry*, *6*(4), 267-285.

In seeking to establish entity vs. incremental theoretical orientations as unique constructs, it is important to empirically differentiate them from other variables. Dweck and colleagues provided evidence in support of theory of intelligence as a unique

construct (Dweck & Bempechat, 1983; Dweck and Leggett, 1988; Elliot & Dweck, 1988). However, comprehensive data collection in support of the measure and its relationship to other variables had not been conducted. Specifically, Dweck et al., (1995) collected a wide variety of demographic data and results on other psychometric instruments and compared them with theory of intelligence to see if the construct could be accounted for by another variable. The results in Table 6 and Table 7 supported the identification of implicit theories of intelligence (mindset) as an independent construct.

Table 6

Measures of Implicit Theories of Intelligence and Their Relation to the Demographic Characteristics of the Respondents

Response: Theory of Intelligence	Model	Estimated Parameters
Study 4	~Sex + Age	β (sex) = -.093, ns β (age) = .032, ns
Study 5	~Sex + Age	β (sex) = -.255, ns β (age) = .120, ns
Study 3	~Political Affiliation + Religious Preference + Church Attendance + Importance of Religion	β (Pol. Affl.) = .096, ns F (Rel. Pref.) < 1 .O, ns β (Church Att.) = .181, ns p (Imp. of Rel.) = .295, ns

a Female coded as 1, male coded as 2b 1 = Democrats, 2 = independents, 3 = Republicans. 'Categories of religious preferences: Protestant, Catholic, Jewish, Other. d 1 = every week, 2 = almost every week, 3 = once or twice a month, 4 = a few times a year, 5 = never. = not important, 2 = somewhat important, 3 = very important

Regardless of demographic factors such as age, gender, or political affiliation, these studies support implicit theories of intelligence measurement as independent from other psychometrics such as cognitive ability or self-esteem. Finally, there was only one statistically significant relationship found and that was between internal control (locus of control) and incremental theories of intelligence. This was to be expected given that

those who had a higher sense of internal control would feel they had more power to control their abilities.

Table 7

Construct Validity of the Implicit Theory of Intelligence Measure

Response Variable	Study Number	Theory of Intelligence
Self-presentational Concerns		
-Self-Monitoring (Snyder, 1974)	5	β = .040, ns
- Social Desirability Scale (Paulhus, 1984)	6	β = .024, ns
Cognitive Ability		
-SAT Scores (Quantitative and Verbal)	5	β =-11.03, ns
Confidence in the Self		
-Confidence in Intellectual Ability	2	β = -.001, ns
	6	β = -.056, ns
- Self-Esteem Inventory (Coopersmith, 1967)	2	β = ,391, ns
Locus of Control		
-Control by Internal Factors (Levenson, 1974)	4	β = .150, p.01
-Control by Powerful Others (Levenson, 1974)	4	β = .059, ns
-Control by Chance (Levenson, 1974)	4	β = -. 114, ns
Optimism		
-Confidence in Other People's Morality	6	β = .110, ns
-Confidence in the World	6	β =-1.71,ns
Social Political Attitudes		
-Right-Wing Authoritarianism (Altemeyer,	6	β = -.078, ns
1981)	6	β = -.064, ns
-Political Conservatism (Kerlinger, 1984, Soc.	6	β = -.087, ns
Att. Scale)	6	β = .101, ns
-Political Conservatism (Kerlinger, 1984,	6	β = -.079, ns
Referent Scale)		
-Political Liberalism (Kerlinger, 1984, Social		
Att. Scale)		
-Political Liberalism (Kerlinger, 1984,		
Referent Scale)		

Note Adapted from: Dweck et al., (1995). Implicit theories and their role in judgments and reactions: A word from two perspectives. *Psychological inquiry, 6*(4), 267-285.

In closing, stage three represented an important milestone in the development of the growth mindset. By publishing significant validity and reliability evidence for the measure of implicit theories of intelligence, Dweck and other researchers amassed

empirical evidence and measurement tools to take the study of the growth mindset to the stage of intervention. Now that researchers could accurately measure implicit theories of intelligence, the next logical step was to attempt to manipulate them.

Stage 4: From Measurement to Intervention: The Growth Mindset

Although Dweck consistently conducted experimental studies to evaluate her hypothesis, only with the development of an instrument to measure theories of intelligence could the final stage of the growth mindset emerge. Once measurement of theories of intelligence was established, Dweck and fellow researchers turned their attention to studying its manipulation. Dweck had already established that participants' goal orientation could be manipulated (Elliot & Dweck, 1988). However, according to Dweck and Leggett's model (1988), manipulating a participant's goal orientation was not directly impacting the underlying psychological process known as theories of intelligence. Evidence that participants' theories of intelligence could be manipulated surfaced in the 1990s with work done by Henderson (1990), Dweck et al., (1995), and Hong, Chiu, Dweck, Lin, and Wan (1999). Early evidence in support of the potential for specific interventions resulted from research done in the area of praise and stereotype threat by Mueller and Dweck (1998) and Steele and Aronson (1995) respectively. The most persuasive evidence in support of the effectiveness of the growth mindset of intelligence theory intervention came with the work of Blackwell et al. (2007), which built on the previously mentioned work.

Dweck's collaboration with Claudia Mueller (1998) in their widely cited article "Praise for Intelligence Can Undermine Children's Motivation and Performance" provided some of the first evidence in support of manipulation of theories of intelligence. In their studies, students praised for intelligence chose more performance goals while

those praised for their efforts consistently chose more learning goal oriented tasks. These students also demonstrated increased attributions in line with the type of praise received. That is, students praised for intelligence produced more ability related explanations in response to failure while those who received the effort praise were more likely to explain failure through attributions based on effort or strategy use. Thus, through specifically designed, measured, and assessed interventions, participants' theories of intelligence were shown to be manipulable.

Research conducted by Aronson et al. (2002) also provided early clues to the powers of theories of intelligence intervention. Aronson and colleagues hypothesized that African American students would be less vulnerable to stereotype threat if they were first exposed to messages regarding the malleability of intelligence. Their study showed that African American (and to some degree white) participants exposed to messages promoting the malleability of intelligence reported greater academic enjoyment, engagement and obtained higher grades.

Hong et al., (1999) sought to integrate Dweck and Leggett model's ability to predict effort attributions with students' willingness to participate in remediation when feedback was suggested in order to establish if the intelligence theories of participants could be manipulated. They conducted three separate studies to explore these research questions. In study one they found that theoretical orientation (entity vs. incremental) did predict effort attributions. Specifically, incremental theorists were more likely to attribute performance to effort. On the other hand, entity theorists were more likely to attribute performance to ability. The second study explored whether a student's theory of intelligence would predict their willingness to take remedial action if feedback suggested

it was necessary. The researchers found in this case that incremental theorists were more likely than entity theorists to pursue remediation in this scenario. Finally, in study three researchers sought to manipulate the student's theory of intelligence by exposing them to a *Psychology Today* article endorsing either incremental or entity beliefs. The researchers found that they were able to manipulate the students' theoretical orientations to a statistically significant degree and that these manipulations resulted in altered likelihoods of the students to take remedial action. In summary, Hong et al., (1999) found evidence that attributions predicted by theoretical orientation (entity vs. incremental views of intelligence) as frameworks for meaning had important implications for the understanding of motivation. This article outlined the important identification of measureable and manipulable orientations that predict effort attributions and resulting action in educational settings. This powerful finding would soon be articulated by Dweck as the growth mindset.

Blackwell et al. (2007) combined the findings of the Henderson and Dweck (1990) study and the Hong et al. (1999) study described above. They took it one step further in a longitudinal study by introducing an experimental intervention to see if they could alter the intelligence theories of the participants and as a result, improve academic achievement as measured by grades in mathematics. Two separate studies were conducted. Study one sought to examine the link between students' intelligence theories and achievement results. Study two evaluated the results of an intervention that sought to change the students' mind sets. In study one, 373 7^{th} graders' intelligence theories were followed over two years. Students who were identified as having a fixed mindset had a flat trajectory of achievement. On the contrary, students who were identified as having an

incremental or growth mindset demonstrated an upward trajectory. Study two taught the incremental mindset to a group of 7th graders (N=48) and simultaneously followed a control group of 7th graders (N=43) over the same period as the first study. As a result, the experimental group demonstrated improved motivation in the classroom compared with the control group, which demonstrated a downward trajectory. Although these findings were statistically significant, Blackwell et al., (2007) noted that the effect sizes for the positive results of the interventions on academic achievement were small. However, the researchers also stated that if these interventions were carried out over the course of a student's educational career, the results could be more powerful.

The work done by Dweck and others through 2007 demonstrated promising results for the growth mindset manipulation resulting in positive achievement outcomes. With the publication of Dweck's (2006) *Mindset, The New Psychology of Success, How We Can Fulfill Our Potential,* Dweck set off a rapid expansion of research into the growth mindset in the area of academic achievement and beyond. Following these early ground breaking studies, Dweck's colleagues and former graduate students along with many others began studies to replicate and expand on her findings. For example, current attempts to teach the growth mindset on a large scale, such as Paunesku's (2013) growth mindset study utilizing Khan Academy and involving 250,000 participants has found success. In closing this section, it is important to note that growth mindset interventions are not seen as a means on their own to improve achievement but rather an important complement to effective instruction. Yeager and Walton (2011) point to the power of social-psychological interventions like the growth mindset as required components of effective instruction.

Beyond Mindset Theoretical Development

Mindset and subgroup factors. The original mindset research reported that mindsets are evenly distributed across demographics (Dweck et al., 1995). Generally stated, Dweck and colleagues have conveyed a 40-20-40 principal (Dweck, 2006), meaning that 40 percent of the population is fixed minded, 20 percent neutral, and 40 percent is growth minded. Despite these assertions, it is important to closely evaluate subgroups against these percentages in order to establish whether or not the examined population follows this distribution. Beyond the distribution of mindsets in a population, it has been established that demographic factors and subgroup classification can impact the degree to which mindset influences academic performance (O'Rourke, Haimovitz, Ballweber, Dweck, & Popović, 2014). The growing number of studies documenting the differing role of mindset based on demographics and subgroup identity demands further attention (Dar-Nimrod & Heine, 2006; Dvorak, 2014; Grant & Dweck, 2003).

When evaluating the correlation between mindset and standardized test performance the role of demographic and subgroup identity as potential moderator variables must be evaluated. Commonly measured demographic variables including, race, ethnicity, socioeconomic status (SES), gender, and year in school must be included in order to isolate the impact of mindset and evaluate any potentially statistically significant differences between groups. The literature suggests that race and SES may amplify the importance of having a growth mindset for increased academic achievement (Blackwell et al., 2007). Specifically, having a growth mindset for minority students of lower SES has a statistically significant positive impact on achievement (Blackwell et al., 2007). Dweck (2008) has also reported mindsets may play a greater role for females when it

comes to math and science achievement and career attainment. Dweck (2000) has speculated that females receive more entity related messages as children based on their behavior ("you are a good girl") when compared to boys, thus promoting the development of a more fixed mindset. This relationship between females and an enhanced role the growth mindset plays in academic success has been found repeatedly (Dar-Nimrod & Heine, 2006; Grant & Dweck, 2003).

Similarly, student GPA, attendance, and educational program classification are included as educational moderators within this study. GPA has consistently been used to evaluate the relationship between growth mindset and academic achievement (Blackwell et al., 2007). It has also been suggested that motivational variables actually play a greater role in GPA than they do in tests scores when compared to intelligence (Duckworth, Quinn, & Tsukayama, 2012). Attendance has also been found to correlate highly with mindset (West et al., 2014). Finally, educational program classification (regular education, special education, and gifted) are a subgroup classification that warrants additional research regarding the role of mindset in academic performance. One study found that students with learning disabilities (identified in special education) are more likely to have a fixed mindset or entity view of intelligence (Baird, Scott, Dearing, & Hamill, 2009). There is also evidence that gifted student's mindsets have less of an impact on their academic performance when compared to their non-gifted peers (Siegle, Rubenstein, Pollard, & Romey, 2009), although other studies have reported that gifted students are equally susceptible to the negative effects of a fixed mindset on academic performance (Ziegler & Stoeger, 2010). By effectively studying the relationship between mindsets

and different demographics and subgroup identities, interventions can be targeted more efficiently to those who would most benefit from them.

Mindset and achievement on standardized tests. This study evaluates the role of mindset, a non-cognitive measure, in predicting performance on a standardized test. The high stakes role of standardized tests in schools brought about by the No Child Left Behind Act (Bush, 2001) now known as the Every Student Succeeds Act, has focused educational research resources on exploring these assessments. Investigating the role of non-cognitive factors in standardized test performance has become increasingly important as policy makers seek financially efficient methods of improving test performance. The role of mindset in academic achievement as measured by grades and grade point average has been consistently documented (Blackwell et al., 2007; Grant & Dweck, 2003). Additional research has been conducted that demonstrates that a growth mindset in women (Good, Rattan, & Dweck, 2007, Rattan, Good, & Dweck, 2012) and African American and Latino students (Aronson et al. 2002; Good et al., 2003) protects against stereotype threat when measuring performance on standardized tests. However, limited research regarding the role of mindset in predicting standardized test performance has been conducted. This study seeks to address this limitation in the literature.

Previous research that has been conducted using non-cognitive traits as predictors of standardized test performance have been inconclusive. One study conducted by Duckworth et al., (2012) demonstrated that standardized test scores correlated highest with IQ while achievement measured by grades correlated higher with measures of self-control. A study conducted by Holmlund and Silva (2009) evaluated English as a second language non-cognitive remediation programs, which included the targeting of self-

confidence, locus of control, self-esteem, and motivation. They found no statistically significant effect on standardized test performance when compared to a control group. On the other hand, Liu, Bridgeman, and Adler (2012) conducted a randomized experiment in which they induced different motivational conditions. This study yielded statistically significant differences in performance (effect size of .68) for those who received the treatment designed to increase motivation. In another study, using the Nebraska State Accountability Test, Dvorak (2014) found a moderate positive correlation between being growth minded and 8th and 11th grade reading scores. Finally, another recent study found that motivation and cognitive strategy use predicted growth of performance on standardized tests more than intelligence (Murayama, Pekrun, Lichtenfield, & Vom Hofe, 2013).

NWEA MAP performance and construct irrelevant variance. An exhaustive review of the literature yielded no studies specifically evaluating mindset and NWEA MAP performance. However, there has been research conducted evaluating the role of effort in NWEA MAP performance and potential negative distortion of results. Negative distortion of results is described as assessment results that are lower than the student's true achievement level (Wise, Ma, Cronin, & Theaker, 2013). Negative distortions are described as threats to the validity of a test score due to construct-irrelevant variance (CIV) (Haladyna, & Downing, 2004). Haladyna and Downing (2004) describe these CIVs as potentially impacting scores positively (increasing a score) or negatively (decreasing scores). An example of positive distortion would be cheating, where an examinee would obtain a higher score than they would without cheating. On the other hand, test anxiety is an example of negative distortion if a score is decreased because the

anxiety does not allow the examinee to demonstrate their true performance. Motivation is another example of a CIV that could play a positive or negative distorting role. Computer adaptive testing's ability to record the time spent on individual items and tests as a whole creates a new method of analyzing student motivation. This method of evaluating student motivation known as response time effort (RTE) provides researchers with a new quantitative tool for evaluating motivation on standardized assessments (Wise & Kong, 2005). While RTE is beyond the focus of this study, it is theorized that higher mindset scores will represent a positive CIV and lower mindset scores represent negative CIV. Thus, it was theorized that this study would identify a statistically significant relationship between mindset scores and NWEA MAP subject test performance based on the CIV theory presented here.

Criticisms of the Growth Mindset. The expanding growth mindset movement is not without its critics. The main vein of criticism regarding the growth mindset has been primarily focused on implementation and integration of mindset theory and interventions into educational environments. Dweck has responded to these criticisms with her own warnings about over simplifying her theory and the importance of proper implementation. Dweck has publicly stated that one of her greatest fears is that mindset becomes the new self-esteem movement (Dweck, 2016).

Perhaps the most passionate and public criticism of the growth mindset movement has come from Alfie Kohn whohas raised criticisms of the growth mindset as an over simplified theory, which over emphasizes the importance of an educator's communication styles, and distracts from overall structural problems within education by putting the emphasis on the student's effort rather than the state of the education system.

Kohn (2015) published an article in Slate Magazine entitled *"*The perils of "Growth Mindset" education: Why we're trying to fix our kids when we should be fixing the system." Kohn made three main critiques of mindset theory, namely the emphasis on effort, teacher praise, and a lack of focus on improving instruction. First, Kohn claims that mindset theory over emphasizes effort to the detriment of the student who may be forced to feel that lack of success is their fault for not putting in sufficient effort. Second, Kohn takes issue with the praise research conducted around growth mindset. He asserts that by emphasizing extrinsic motivation in the form of teacher praise in an effort to promote student learning, educators will unwittingly decrease intrinsic motivation. Third, Kohn raises the concern that by emphasizing traits internal to students, educators are tempted to abdicate their responsibility to work to improve the system within which that student is learning.

While well-articulated, Kohn's criticism lacks empirical challenge to Dweck's work and instead focuses on historical and policy debates, which while important, do not detract from Dweck's findings. On one point, Dweck does agree with Kohn. She has stated a number of times that she believes that the concept of the growth mindset has been over simplified and that the role of effort has been over emphasized to the detriment of other important aspects of a growth mindset, namely the application of strategies and the seeking of guidance from others (Dweck, 2015, 2016).

Others criticize the growth mindset not for its theoretical underpinnings but for its inadequate implementation in schools. Peter Dewitt (2015) cites work done by John Hattie claiming low effect sizes for growth mindset interventions in his claim that mindset interventions are not living up to their hype. Dewitt's primary argument is that

educators are only paying lip services to mindset theory by changing their language but not their underlying beliefs which are communicated non-verbally and through classroom instructional practices. Dewitt emphasizes that teachers must reevaluate their own deeply held beliefs, before they can pass on a growth mindset to their students. He goes further to note that instructional and assessment practice must change as well if the school culture is to shift to one based on the core values of the growth mindset. Dweck herself in recent writings and presentations has begun to echo these same concerns (Dweck, 2016).

Concerns regarding the misapplication of Dweck's theory have also been raised by researchers, journalists and Dweck herself. The most important misconception is that mindset is synonymous with effort. Dweck cautions parents and educators alike that it is important to emphasize effort by praising specific aspects of the learning process and strategies and tying them back to the learning outcome rather than just effort itself (Barshay, 2015). Dweck also urges parents and educators to evaluate their own response to challenges and failures to ensure they are modeling a growth mindset. According to Dweck, only by constantly monitoring one's own growth and fixed mindset triggers and responses can one hope to model the growth mindset and instill it in others (Dweck, 2016).

Chapter III: Methods

This quantitative cross-sectional study investigated the relationship between mindset and performance on the NWEA MAP assessment. The study combined secondary data and survey data within the analysis. The statistical relationship between mindset and NWEA MAP performance and the mediation of control variables was evaluated throughout this study. Gender, ethnicity, race, socioeconomic status, special education participation, gifted education participation, grade point average, attendance, and year in school were used as control variables.

*Research Question***:** What is the relationship between mindset (entity vs. incremental beliefs) and student performance on the Northwest Evaluation Association's (NWEA) Measure of Academic Progress (MAP)? In order to respond to this overarching research question, the researchers addressed the following questions: 1) what is the relationship between mindset (entity vs. incremental beliefs) and student performance on the Northwest Evaluation Association's (NWEA) Measure of Academic Progress (MAP)? 2) What is the relationship between subgroup factors (demographics, academic program, and academic achievement measure by GPA, attendance, and year in school) and mindset's ability to predict student performance on the NWEA MAP?

Hypotheses

Null Hypothesis #1: There is no statistically significant relationship between mindset and student performance on the NWEA MAP.

Null Hypothesis #2: There is no statistically significant relationship between subgroup factors and the ability of mindset to predict performance on the NWEA MAP.

Overview of the Current Study

In order to evaluate the research question, a cross-sectional design was utilized. The study drew on both archival data from the school and survey data collected as part of this study. The archival data consisted of parent supplied demographic information from the school's enrollment process and educational records including achievement data, educational program facts, number absences, and NWEA MAP assessment results. The survey data was collected by the researcher with the cooperation of the school staff. The participants were middle school students in grades 6-8 in a college preparatory charter school in a metropolitan area of the southwestern United States. The survey instrument used to establish mindset scores was Dweck's *Implicit Theories of Intelligence Scale for Children* (Dweck, 2000).

The study explored the findings through estimated bivariatecorrelations and a series of nested multiple regression models to answer each question. The primary research question sought to evaluate the relationship between mindset (independent variable) and student performance on the NWEA MAP subject tests (dependent variable). Mindset's relationship to NWEA MAP subject tests was first evaluated through descriptive statistics and estimated bivariate correlation matrices. The second phase of data analysis relied on multiple regression analysis to evaluate the impact of control variables on mindset as a predictor of student performance on the NWEA MAP. The secondary research questions were explored using similar techniques in order to identify potential mediating variables.

Participants

The participants for this study were drawn from a high achieving college preparatory charter school in a metropolitan area of the southwestern United States. The students attending this school were selected through a lottery system. The only allowed preference for enrollment is sibling preference, which guarantees enrollment for siblings of students selected through the lottery. The participants were drawn from grades 6-8. Participation in the study was voluntary and open to all students enrolled in these grades. This sample is in part a convenience sample due to the researcher's access to the facility but is also purposive in that the study seeks to evaluate the applicability of previous research to this setting (high achieving charter schools). At the time of the study, the school had a 6^{th}-8^{th} grade population of 333 students. Of those students, 307 students were present on the day of the study, consented to participate, and had completed the NWEA MAP assessments. Table 8 provides descriptive statistics for the participants. Further review of these descriptive statistics can be found in the results section.

Table 8

Participant demographics

Variables (N=307)	Variable Categories	Frequency	%
Gender	0=Male	140	45.6
	1=Female	167	54.4
Year In School	6th Grade	101	32.9
	7th Grade	103	33.6
	8th Grade	103	33.6
Special Education	0=Not in Special Education	291	94.8
	1=Special Education	16	5.2
Gifted	0=Non-Gifted	246	80.1
	1=Gifted	61	19.9
Socioeconomic Status	0=Not Title I Eligible	275	89.6
	1=Title I Eligible	32	10.4
Ethnicity	0=Non-Hispanic	205	66.8
	1=Hispanic	102	33.2
Race	1= Caucasian	274	89.3
	2=African American	11	3.6
	3=Asian	12	3.9
	4=Pacific Islander	5	1.6
	5=Native American	5	1.6

In designing the study, the researcher proposed building regression models for 1-14 predictor variables. The proposed multiple regression models required a determined number of participants in order to have sufficient power to identify effect sizes as can be seen in Table 9. The A-priori calculations identifying the proposed sample size allowed for the identification of conventionally accepted effect size parameters: small (.02), medium (.15), and large (.35).

Table 9

Sample size power calculations.

N	Power	Probability level	Number of predictor variables	Attainable effect size
309	.8	.05	1	.025
307	.8	.05	14	.062

Note: Values were calculated using: Soper, D.S. (2015). A-priori Sample Size Calculator for Multiple Regression [Software]. Available from http://www.danielsoper.com/statcalc

Instrumentation

The instruments used for this study are established instruments with published validity and reliability data. De-identified student demographic and educational information was obtained from the school staff through the student information system (SIS). Finally, standardized test scores for the fall 2015 administration of the NWEA MAP were obtained as part of de-identified secondary archival data provided by the school.

The *Implicit Theories of Intelligence Scale for Children* (Dweck, 2000) is the primary scale for identification of entity vs. incremental beliefs. The scale was developed by Dweck (2000) and her colleagues. They were primarily responsible for the theoretical development of the constructs and have been the principal researchers in this area. The NWEA MAP assessment (2004) was selected because it assesses student achievement on Common Core State Standards (National Governors Association Center for Best Practices & Council of Chief State School Officers, 2010) and is normed on a national scale involving students from all 50 states.

Implicit Theories of Intelligence Scale for Children (ITISC) is a six item inventory measured on a six-point Likert-type scale (Dweck, 2000). The first three items of the scale can be used in isolation as a brief form. The inventory measures students' beliefs

about intelligence as an entity (immutable) trait or an incremental (mutable) trait. Scores of 1-3 indicate entity beliefs, scores of 5-6 indicate incremental beliefs, and scores greater than 3 and less than 4 are recognized as mixed beliefs. Incremental items (4-6) are coded as 6 points for strongly agree, 5 points for agree, 4 points for mostly agree, 3 points for mostly disagree, 2 points for disagree, and 1 point for strongly disagree. Entity items (1-3) are coded as 1 point for strongly agree, 2 points for agree, 3 points for mostly agree, 4 points for mostly disagree, 5 points for disagree, and 6 point for strongly disagree. Points are totaled and divided by 6 in order to obtain the results. Entity (fixed) vs. incremental (growth) beliefs are also referred to in this dissertation as the measure of growth mindedness.

According to Dweck et al., (1995), the internal reliability of the ITISC items ranged from .94 to .98. The test-retest reliability score with a two-week interval was .80. Dweck (2000) and colleagues have also provided clear validity evidence in the literature. First, the authors explored validity evidence based on response process related to the measure. Citing Henderson (1990), Dweck (2000) explained that validation studies yielded qualitative explanations for items responses that corresponded with the item choice. The explanations provided by the subjects paralleled the responses provided on the scale. Internal structure validity evidence was collected through factor analysis further supporting the validity of the measure (Dweck et al., 1995). See Appendix A for a copy of the measure.

The Northwest Evaluation Association (NWEA) Measure of Academic Progress (MAP) is a short cycle Common Core-aligned computer adaptive assessment administered in the fall, winter and spring in K-12 settings. The assessment provides

instructionally relevant feedback to teachers and students in the areas of math, reading, and language. According to the NWEA (2004), test-retest rates of reliability range from the mid .80s to .90 across grade levels as measured by Pearson's estimated correlational coefficient. Content and concurrent validity information provided by NWEA (2004) suggest alignment with tested standards and other assessments.

The school's Student Information System (SIS) was the source for all additional data. School-based student information systems store demographic and educational information. Student demographics are supplied by students and families through online enrollment software and then uploaded. Academic program and achievement information is entered on an ongoing basis by the teachers and staff members. The following data were obtained from the school through the SIS: gender, ethnicity, race, SES, special education program participation, gifted program participation, GPA, attendance, and year in school. NWEA MAP results in the areas of math, reading, and language were also provided by school staff members via the SIS.

Table 10

Variables to be used in regression models by type

Code	Variable	Type	Independent/Dependent
HISP	Hispanic Ethnicity	Categorical	Independent
REID	Racial identification (recoded into dummy variables in SPSS)	Categorical	Independent
GEN	Male/Female	Categorical	Independent
GPA	Semester progress report grade point average (GPA)	Continuous	Independent
ATTEN	School attendance as of progress report	Continuous	Independent
SPED	Special Education Traits	Categorical	Independent
GIFT	Students are in the Gifted Prog.	Categorical	Independent
SES	Title I participation	Categorical	Independent
YINSC	Year in school (6-8)	Categorical	Independent
ITISCS	Total score on Implicit Theories of Intelligence Scale for Children	Categorical	Independent
MMAP	NWEA MAP Math subject test performance percentile score	Continuous	Dependent
RMAP	NWEA MAP Reading subject test performance percentile score	Continuous	Dependent
LMAP	NWEA MAP Language subject test performance percentile score	Continuous	Dependent

Procedure

This study is cross-sectional in nature in that data were collected within a short period of time in order to evaluate the relationship between mindset and student performance on the NWEA MAP. Students completed the surveys, the NWEA MAP, and had their demographic information collected in the first semester of the school year. The following procedures represent the actual steps taken as outlined in the submitted institutional review board protocol. The study procedures are presented in a numbered list for clarity and simplicity of replication.

1. **Step 1:** Following approval from the university IRB office, the study information was communicated to families through digital and hard copy communications two

weeks prior to the planned collection of survey data. Parents/guardians were provided the informed consent information in this communication (the researcher was granted an alteration of the parental consent requirement by the university IRB. Written parental permission was not required by the IRB).

2. **Step 2:** Students were surveyed in their advisory classes (student assent was sought at the time of the survey). Advisory class is a combination of study hall and homeroom. Assent from students for participation in the study including permission to access secondary school data was requested at the time of the survey. The survey took place during the students' advisory period which is the last period of the day. Teacher advisors facilitated student participation in the survey or the alternate activity if the student declined to assent. Links for the survey/alternate activity were emailed out to each student prior to their advisory period. All student interaction with the study took place through their email and over the internet with the survey delivered via an online google form.
3. **Step 3:** The researcher obtained de-identified student information from the school (secondary data) for the students who assented to participate in the study and whose parents did not opt them out of the study.
    a. Data access procedure: Survey information was not evaluated until it was de-identified through the following process.
        i. Student survey information was used to populate a spreadsheet. The first 2 columns of the sheet were participant number and name.
        ii. One copy of the first 2 columns linking participant number to student ID was printed in order to use as a key for requesting

student information (secondary data set) from the school. Researchers retained the survey information identified only by participant number. Survey responses were all Likert scale responses and thus no identifiable information remained in the survey data set.

iii. The school used the provided key to construct the secondary data set identified only by participant number.

iv. The school was instructed to destroy the key linking students to participant number. The researcher did not retain a copy of the key.

v. The secondary data provided by the school therefore included only unidentifiable data and thus was not subject to the FERPA requirement of written consent (see alteration of consent explanation).

b. Based on consenting/assenting participants identified, the following information was provided by the school in the secondary data set to the researcher. Participants were identified by participant number only.

i. Demographics (gender, ethnicity, race, year in school, SES)

ii. Ed. Program (special education, gifted education, regular education)

iii. GPA

iv. Attendance (number of unexcused absences by period)

v. Time on test (measured in minutes used to complete the MAPS test)

vi. NWEA MAP Assessment results for math, language, and reading tests.

4. **Step 4:** Any student who did not provide assent or whose parent/guardian opted them out of the study after data was collected had their information excluded from the data set and survey results deleted with all hard copies destroyed.
5. **Step 5:** The researcher then combined the survey data with the school provided secondary data for those participants who assented and whose parents had not opted them out of the study. Student survey responses were matched to the data set by participant number.
    a. Once the secondary and survey data was combined, participant's numbers were randomly changed again in order to further reduce any potential breach of confidentiality.
6. **Step 6**: The researcher analyzed the data set according to previously stated research questions, hypotheses, and outlined data procedures. The findings were recorded, analyzed, and discussed in this document.
7. **Step 7**: The researcher offered to provide school staff with Growth Mindset professional development at the school's request.

Informed consent. Participation in the study was voluntary. Given that the participant population was under the age of 18, both informed consent and informed assent were required. Participants and families in grades 6-8 were informed of the study in a letter through the school email system and were provided a hard copy. All participants had family emails provided by the school (school domain specific Gmail accounts) and families were familiar with the school expectation to monitor the email on a regular basis. Given that the nature of the data collected (surveys, educational program,

and achievement data) is a part of the participants' regular experience at the school, this research was deemed to be of minimal risk. Because of the established minimal risk, an alteration of the informed consent procedure was sought and granted by the university IRB. This alteration allowed for informed consent to be achieved through parental notification, requiring parents or students to actively opt out if they did not want to participate. The letter distributed served as informed consent and included the required components of informed consent. Informed assent was obtained from students at the time of the administration of the survey. Students read the informed assent letter as the first step in the survey process. If students chose not to provide assent they were thanked and their survey reverted to the alternate activity. This informed assent letter was based on the informed consent letter to parents but was modified to ensure it was age appropriate for the participants.

Informed consent was sought two weeks prior to the start of the study and no data collection was conducted until the informed consent procedures were completed. The school provided the researcher with an email account, which was included in the informed consent letter in order to facilitate communication between the families, the participants, and the researcher. Questions were answered and withdrawal of informed consent (opt outs) were collected via this email address. After the participants were presented with the student survey no additional opt out requests were received.

Survey completion. All students in 6th through 8th grades in the school population were assigned to an advisory period, which functioned as a combined homeroom and study hall. The survey was disseminated during the advisory period and the survey was facilitated by the advisory teachers who had no access to survey results.

The surveys were administered through computers via an online survey Google Form developed in Google docs, an online tool affiliated with the school's Gmail domain The survey was delivered directly to the students' individual email accounts and was sent from an email created specifically for the purpose of this study and provided by school officials (research@schoolsname.org). Student participation was tracked through their individual email addresses, which automatically populated a Google Sheets document with responses. Participant email addresses were then converted to their individual participant number in order to anonymize the data while still making it possible for school officials to provide the data connected to the participant's survey information.

The survey form was partitioned, requiring participants to read and assent to the study prior to being able to complete the survey. Those participants who did not assent received a message thanking them for their time and they were provided a link to a study skills-related online reading as an alternate task. Advisory teachers were instructed to ensure that participants had privacy during the completion of the survey or the alternate activity to ensure participants did not feel obligated to participate. It was calculated that students would be able to complete the assent document reading and the Implicit Theories of Intelligence scale in 10 minutes. In order to ensure that participants had sufficient time, 30 minutes were scheduled in the technology environment. Students were instructed to bring along a book to read when they finished. Participant surveys were collected in October which overlapped with the end of the NWEA MAP assessment window. In order to minimize the time for the survey, the brief three item version of the scale was used. The student mindset scores were calculated using these first three items of the ITISCS which can be used in isolation (Dweck, 2000). Thus, individual

participant mindset scores were the average on these 3 items. Cronbach's Alpha for this survey were calculated using SPSS and resulted in a .788.

Data collection. Secondary, de-identified data was obtained from the school in order to construct the comprehensive data set for analysis. The researcher added a participant number to student survey results, the student name and participant number were provided to the school personnel. School officials combined secondary data to the participant number and student name spreadsheet provided. After the secondary data were added, the student name column was deleted by the school prior to providing the data set to the researcher. The researcher did not retain a copy of the key linking the student to participant ID and thus only received unidentifiable student information. This was combined with the survey data by the researcher according to participant number. There were two sources of the participant data provided by the school. The first was student demographic information (i.e. gender, race, ethnicity, SES, and grade level), which was provided by parents/guardians upon enrollment of their students. The second data type was educational program, GPA, attendance, and assessment information, which was collected and entered into the Student Information System (SIS) by school staff.

All archival and survey data was combined into one spreadsheet once the secondary data set was obtained from the school. After the data was combined, the identities of the participants were converted to a new participant number in order to promote confidentiality. This newly created spreadsheet contained student survey information and school provided secondary data which contained no identifiable data. For a complete list of the data collected, see the codebook in Appendix B.

Analysis. The collected data was analyzed using IBM SPSS (v22) and Microsoft Excel (2007). The collected data was screened and related assumptions were checked. Appropriate statistical procedures relevant to each research question and tests of the null hypotheses were conducted. Specifically, nested taxonomies of regression models were fit and analysis of variance was conducted. Final data analysis procedures deployed in this study followed the research question and appropriately fit the collected data.

Data screening and assumption testing. Appropriate data screening techniques as outlined by Tabachnick and Fidell (2013) were conducted. Examples of data screening requirements include evaluating the amount and distribution of missing data, checking for outliers, evaluating residuals, and identifying the procedure for dealing with missing data (impute mean, etc.). Assumptions related to multiple regression and analysis of variance were checked. These procedures include tests for normality, linearity, homoscedasticity, and homogeneity of variance (Tabachnick & Fidell, 2013). All data screening procedures were recorded and relevant information was included in the results chapter.

Appropriate statistical procedures were utilized in order to answer the research question. These included calculating descriptive statistics, general linear modeling, and analysis of variance procedures. Examples of descriptive statistics for continuous variables include range, mean, and standard deviations. Examples of descriptive statistics for categorical data include frequency tables, proportions, and histograms. A nested taxonomy of regression models was fitted to evaluate the question predictor (mindset) against NWEA MAP performance, controlling for subgroup factors. Table 11 describes the theoretical approach in designing the planned multiple regression analysis. Table 12

describes the planned taxonomy of nested regression models and the variables included in the models.

Table 11

Theoretical Framework for Regression Models

Level	Predictor	Literature References
High Priority: Question Predictor Model 1	Intelligence Beliefs (Continuous and Categorical)	Academic Achievement: Dweck & Legget, 1988; Blackwell et al., 2007; Paunesku, 2013; Romero, Paunesku, & Dweck, 2011; Paunesku et al., 2015; Yeager & Walton, 2011; Yeager, Walton, et al., 2013 Assessment: Dvorak, 2014; Liu et al., 2012; Murayama et al., 2013
Medium Priority: Primary Control Predictors Models 2 & 3	Race, Ethnicity, SES	Aronson et al., 2002; Good et al., 2003; Good et al., 2007; Blackwell et al., 2007; Dar-Nimrod & Heine, 2006; Grant & Dweck, 2003; Dvorak, 2014; O'Rourke et al., 2014
Medium Priority: Primary Control Predictors Model 4	SPED, Gifted	Baird et al., 2009; Ziegler & Stoeger, 2010
Low Priority: Secondary Control Predictors Model 5	GPA, Attendance, Year in School	Blackwell et al., 2007; Duckworth et al., 2012

Table 12

Multiple Regression Data Analysis Procedures

Model	**Dependent Variable**	**Independent Variable**	**Control Variable(s)**	**Analysis**
Model 1	MAP scores (by subject)	Mindset		1.Descriptive statistics 2. Estimated Correlation Matrix 3. Simple Linear Regression
Model 2	MAP scores (by subject)	Mindset	1.Demographics: Gender, Ethnicity, Race	1.Descriptive statistics 2. Estimated Correlation Matrix 3. Multiple Regression:
Model 3	MAP scores (by subject)	Mindset	1.Demographics: Gender, Ethnicity, Race 2. SES (Title I)	1.Descriptive statistics 2. Estimated Correlation Matrix 3. Multiple Regression:
Model 4	MAP scores (by subject)	Mindset	1.Demographics: Gender, Ethnicity, Race 2. SES (Title I) 3. Educational Program: Special Education, Gifted	1.Descriptive statistics 2. Estimated Correlation Matrix 3. Multiple Regression
Model 5	MAP scores (by subject)	Mindset	1.Demographics: Gender, Ethnicity, Race 2. SES (Title I) 3. Educational Program: Special Education, Gifted 4. GPA, Attendance, Year in School	1.Descriptive statistics 2. Estimated Correlation Matrix 3. Multiple Regression:

The results of the statistical procedures are presented in the results section.

Aggregate descriptive statistics and estimated bivariate correlation tables are presented

first. The relationships identified in the estimated bivariate correlation matrices were used to construct the multiple regression model. Next, the nested taxonomy of five multiple regression models per subject tests are presented organized by dependent variables; Math, Reading, and Language MAP subject tests.

Concluding Remarks

This study was intended to evaluate the relationship between mindset and student performance on the NWEA MAP assessment. The impact of subgroup traits on the ability mindset to predict performance on standardized tests was also analyzed. With this research completed, the hope is that future studies will be able to target specific subgroups in order to more efficiently focus mindset interventions.

Chapter IV: Results

The purpose of this quantitative correlational study was to evaluate the relationship between student's Implicit Theories of Intelligence Scale for Children results and performance on the NWEA Measure of Academic Progress academic achievement test. The cross-sectional data collected was analyzed and the results are presented in this chapter. The chapter is divided into the following sections: sample description, research question findings, and concluding remarks. Statistical analyses are presented in the following order organized by dependent variable (NWEA MAP subject test): descriptive statistics, estimated bivariate correlation matrices, multiple regression models, analysis of variance results, and prototypical plots highlighting interesting relationships.

Research Question

What is the relationship between mindset (entity vs. incremental beliefs) and student performance on the Northwest Evaluation Association's (NWEA) Measure of Academic Progress (MAP)? The evaluation of this research question included the analysis of subgroup factors (i.e. demographics, socio-economic status, academic program: special education and gifted education, academic achievement measured by GPA, attendance, and year in school) and their impact on mindset's ability to predict student performance on the NWEA MAP.

- **Null Hypothesis #1:** There is no statistically significant relationship between mindset and student performance on the NWEA MAP.
- **Null Hypothesis #2:** There is no statistically significant relationship between subgroup factors and the ability of mindset to predict performance on the NWEA MAP.

Five nested hierarchical regression models were constructed for each subject assessment in order to test the above null hypotheses. These models represent 3 levels of

question predictors grounded in the literature. Table 13 represents the theoretical framework for the construction of the regression models.

Table 13
Question Predictor and Control Variable Framework for Regression Models

Level	Predictor
High Priority: *Question Predictor* Model 1	Intelligence Beliefs (Continuous and Categorical)
Medium Priority: *Primary Control Predictors* Models 2 & 3	Gender, Race, Ethnicity, SES
Medium Priority: *Primary Control Predictors* Model 4	SPED, Gifted
Low Priority: *Secondary Control Predictors* Model 5	GPA, Attendance, Year in School

Study Sample

The sample in this study includes 307 middle school students attending a college preparatory charter school in a metropolitan area of the southwestern United States. Student enrollment was dependent on lottery selection and was open to students across the state. The only recognized lottery preference was for students applying who already had a sibling enrolled in the school. Apart from this lottery preference, the selection of the students was random. However, student inclusion in the lottery was solely based on family self-selection into the lottery. Furthermore, the lottery process is conducted entirely online and promotional information is only available in English. The school offers transportation services from varying locations across the metropolitan area. School officials explained that no promotional recruitment efforts had been conducted over the

previous 3 years beyond the school's website due to the high demand for student enrollment. This information is provided in order to contextualize the demographic makeup of the school, which is reported in Table 15.

The entire middle school population was targeted for this study. On the day that the students were presented with the survey and their assent to participate in the study was requested, there was a total of 333 students present. Of those, 312 students assented (or had not previously been opted out by their parent/guardian) to participate, representing a 93.69 percent participation rate. Five students were excluded from the study because they were not present at school for the NWEA MAPS test and therefore had no assessment data. The existing data of these five students obtained from the school was reviewed and no discernable pattern was detected and therefore it was determined they did not represent systematic error. These five participants were excluded from the analysis. All participant data were reviewed and no significant outliers were detected. Therefore, the remaining 307 participants were retained in the dataset.

Table 14

Descriptive Statistics for the Continuous Variables

Variables (N=307)	Mean	SD	Min	Max
Math MAP Percentile (MPILE)	59.81	22.26	3.0	99
Math MAP RIT (MRIT)	226.98	13.21	188	259
Math MAP Time (MTIME)	58.88	20.59	11	191
Reading MAP Percentile (RPILE)	68.49	23.02	1	99
Reading MAP RIT (RRIT)	222.84	13.14	163	254
Reading MAP Time (RTIME)	53.31	21.53	8	103
Language (LPILE)	66.82	21.79	1	99
Language MAP RIT (LRIT)	220.30	10.73	178.0	245.0
Language MAP Time (LTIME)	40.57	13.36	8.0	103.0
Total score on Implicit Theories of Intelligence Scale for Children (ITISC)	3.87	1.22	1	6
Grade Point Average (GPA)	3.27	.7715	0	4.22
Attendance (ATTEN): Periods Missed	7.5251	9.59434	0	65

The sample's mean test performance as measured by their performance on the NWEA MAP assessment of achievement indicates that the students were academically advanced when compared to their peers across the country. Percentile scores are reported based on 2011 NWEA MAP national norms. Aggregate student Math, Reading, and Language percentile scores were in the 60^{th}, 68^{th}, and 67^{th} percentiles respectively. Furthermore, the sample mean GPA of 3.27 (sd=.77) also indicates that the sample was advanced academically, which may be explained by student self-selection into the lottery of the charter school because of its college preparatory nature. Due to the school's demographic makeup and academically advanced mean performance, generalizability of these findings will be limited.

Table 15.

Descriptive Statistics of the Categorical Variables

Variables (N=307)	Variable Categories	Frequency	%
Gender (GEN)	0=Male	140	45.6
	1=Female	167	54.4
Year In School (YINSCH)	6th Grade	101	32.9
	7th Grade	103	33.6
	8th Grade	103	33.6
Special Education	0=Not in Special Education	291	94.8
	1=Special Education	16	5.2
Gifted	0=Non-Gifted	246	80.1
	1=Gifted	61	19.9
Socioeconomic Status (SES)	0=Not Title I Eligible	275	89.6
	1=Title I Eligible	32	10.4
Ethnicity (HISP)	0=Non-Hispanic	205	66.8
	1=Hispanic	102	33.2
Race	1= Caucasian	274	89.3
	2=African American	11	3.6
	3=Asian	12	3.9
	4=Pacific Islander	5	1.6
	5=Native American	5	1.6
Total score on Implicit Theories of Intelligence Scale for Children(ITISC)	1=Entity Beliefs	89	29
	2=Neutral	59	19.2
	3=Incremental Beliefs	159	51.8

The sample included 46% males (n=140) and 54% females (n=167). The sample participants were evenly represented across grade levels, 6th (n=101), 7th (n=103), and 8th (n=103) grade students. The ethnicity profile of the sample included 33% Hispanic students (n=102) and 67% non-Hispanic students (n=205). Eighty-nine percent of the

participants were Caucasian (n=274), 4% African American (n=11), 4% Asian (n=12), 2% Pacific Islander (n=5), and 2% Native American (n=5). The socioeconomic status of participants was measured by student eligibility for Title I services. Title I eligibility was calculated based on the total family income and the number of individuals in the family. Title I program participants are considered at risk due to their lower socioeconomic status. Ten percent of students (n=32) were classified as eligible for Title I services compared with 90% of students (n=275) who were not eligible. The sample included 20% of students (n=61) identified as receiving state recognized gifted education services compared to 80% (n=246) who were not receiving gifted services. Students participating in special education as defined by the federally recognized categories represented 5% of the sample (n=16) compared to 95% of the sample (n=291) who were not identified as students receiving special education. In Table 16, students identified as special education students where more consistently identified as fixed minded (62.5 %) according to the ITISCS results when compared to their non-special education peers (27%).

Table 16

Special Education Mindset Frequencies

	SPED (N=16)	Non-SPED (n=291)	Total	Predicted
Fixed	62.50% (N=10)	27.14% (N=79)	28.99% (N=89)	40%
Neutral	.06% (N=1)	19.93% (N=58)	19.21% (N=59)	20%
Growth	31.25% (N=5)	52.92%(N=154)	51.79% (N=159)	40%

Research Question Analyses

Descriptive and inferential statistics were calculated in order to answer the research question and test the null hypotheses. The following section will review the research question, provide the results of the hypothesis testing, and review the statistical

procedures calculated. Both null hypotheses 1 and 2 were rejected as statistically significant relationships were identified.

Research Question. What is the relationship between mindset (entity vs. incremental beliefs) and student performance on the Northwest Evaluation Association's (NWEA) Measure of Academic Progress (MAP)? The evaluation of this research question included the analysis of subgroup factors (demographics, socioeconomic status, academic program: special education and gifted education, academic achievement measured by GPA, attendance, and year in school) and their impact on mindset's ability to predict student performance on the NWEA MAP.

- Null Hypothesis #1**:** There is no statistically significant relationship between mindset and student performance on the NWEA MAP.
- Null Hypothesis #2: There is no statistically significant relationship between subgroup factors and the ability of mindset to predict performance on the NWEA MAP

Both null hypotheses were rejected according to the results of the statistical procedures conducted. Statistically significant relationships between math, reading, and language performance on the NWEA MAP assessment and participant mindset scores were identified through Pearson's and Spearman's estimated bivariate correlation procedures, multiple regression analysis, and analysis of variance procedures. Furthermore, this relationship was impacted based on subgroup factors identified through estimated bivariate correlation matrices and nested hierarchical multiple regression analysis. These relationships are described below.

Estimated bivariate correlations. All variables were included in one comprehensive estimated bivariate correlation matrix in order to evaluate the relationships between all variables. Pearson's correlations were estimated for all

continuous variables and Spearman correlation coefficients were estimated for categorical variables. While all correlations were estimated in one comprehensive matrix, they are presented here in separate estimated bivariate correlation tables in order to facilitate their display and for ease of interpretation. All statistically significant relationships identified in the comprehensive matrix are included here. Furthermore, all variables' correlations with the dependent variables (NWEA MAP results) and the highest level question predictor (mindset) are reported.

Each of the bivariate correlation matrices are presented and the most interesting relationships as they relate to the research questions are highlighted. The results of the estimated bivariate correlation matrices support the rejection of the null hypotheses. The first null hypothesis stated there was no statistically significant relationship between mindset score on the ITISCS and NWEA MAP performance. The following estimated bivariate correlation matrices show that there was in fact a statistically significant relationship between mindset scores and student performance on all NWEA MAP subject tests when estimating Spearman's and Pearson's correlational coefficients. This result was present when calculating mindset as a continuous variable (1-6 scores) and when calculating mindset as a series of categorical variables (fixed vs. growth). The supporting statistics are presented in this chapter.

The second null hypothesis stated that there was no statistically significant relationship between subgroup factors and the ability of mindset to predict performance on the NWEA MAP. The following estimated bivariate correlation matrices indicate that there was in fact a number of statistically significant relationships that impacted mindset's ability to predict performance across all NWEA MAP subject tests. Clear

groups of variables emerged from the results demonstrating that there are variables that correlate with higher NWEA MAP performance beyond mindset scores and other variables that correlate with lower NWEA MAP performance beyond mindset scores. These individual correlations and their level of statistical significance are evaluated in Table 17. Correlation coefficients for a two tailed test between dependent variables Math, Reading, and Language percentile performance on the NWEA MAP assessment and independent variables mindset score, attendance, and GPA are also presented in Table 17.

Table 17

Estimated Pearson's Correlation Coefficients for Continuous Variables

	Math Map %ile	Reading Map %ile	Language Map %ile	ITISCS	Absences	GPA
Math Map %ile	-					
Reading Map %ile	.645***	-				
Language Map %ile	.511***	.580***	-			
ITISCS	.228**	.236***	.244***	-		
Attendance	-.054	-.020	-.075	-.175**	-	
Grade Point Average	.505***	.539***	.425***	.167**	-.207***	-

~p<.10, *p<.05, **p<.01, ***p<.001

Of the three NWEA MAP subject tests: Math, Reading, and Language, mindset scores all had a small to moderate positive correlation (.288,.236, and .244 respectively) at a p value <.001 with mindset. The results suggest that the higher a student's mindset score, the higher the percentile performance will be across subject tests. Grade Point Average (GPA) had a large estimated correlation with Math (.505) and Reading (.539) subject tests at p<.001. While GPA and MAP Language performance had a moderate to large estimated correlation (.425) at a p<.01. Each of the MAP subject tests had large estimated correlations with each other at statistically significant p values (<.001). The GPA and inter-MAP estimated correlations are to be expected as theory suggests that

these values would correlate with latent factor *g*. Furthermore, GPA and mindset demonstrated a small positive estimated correlation (.167) at p<.01.

Table 18 evaluates the relationships between race, MAP performance, and mindset. Race as an independent control variable, mindset as the independent predictor variable and NWEA MAP subject test percentile performance as the dependent variable are presented.

Table 18

Mindset, NWEA MAP Performance, and Racial ID Estimated correlations (Spearman's)

	Math Map %ile	Read Map %ile	Lang Map %ile	ITISCS	Cauc.	Afr. Amer.	Asian	Pac. I.	Nat. Amer.
Math Map %ile	-								
Read Map %ile	.627**	-							
Lang Map %ile	.449**	.508**	-						
ITISCS	.229**	.234**	.244**	-					
Caucasian	-.008	.013	-.034	.040	-				
African Amer.	-.107	-.107	-.099	-.118*	-.555**	-			
Asian	.007	.014	.054	-.006	-.581**	-.039	-		
Pacific Islander	.119*	.104	.048	.022	-.371**	-.025	-.026	-	
Native American	.047	.000	.097	.062	-.371**	-.025	-.026	-.017	-

~p<.10, *p<.05, **p<.01, ***p<.001

As expected GPA and MAP scores were highly correlated as stated above, which further supports the predictive validity of mindset score when related to overall academic achievement. These findings support the rejection of both null hypotheses. Attendance did not have a statistically significant relationship with any of the dependent variables but did have a small to moderate, negative estimated correlation with mindset (-.207) at a p

value<.01 (.002). While this estimated correlation is interesting, its evaluation is beyond the scope of this study.

Table 18 presents a small negative Spearman's estimated correlation (-.118) between African American identification and mindset at p value<.05(.039). This estimated correlation indicates that within the sample, being African American correlated with having a lower mindset score. There was also a small positive Spearman's estimated correlation (.119) between Pacific Islander identification and Math MAP percentile score at a p value<.05 (.038). Thus, in this sample, being a Pacific Islander correlated with a high percentile ranking. While these findings are statistically significant, the effects are small and generalizability is limited given the small representation of these racial identifications in the sample size (African American n=11 and Pacific Islander n=5). These findings support the rejection of both null hypotheses given the evidence that racial identification correlates with mindset, it is predicted that this would impact mindset's ability to predict MAP performance.

Table 19 presents mindset, NWEA MAP performance, and ethnicity estimated correlations. The table displays small to moderate negative Spearman's estimated correlations between Math MAP percentile and Reading MAP percentile scores for participants that identify as Hispanic (-.201 and -.155).

Table 19

Mindset, NWEA MAP Performance, and Ethnicity Identification Estimated correlations (Spearman's)

	Math Map %ile	Read Map %ile	Lang Map %ile	ITISCS	Hispanic 1/0
Math Map %ile	-				
Read Map %ile	.627**	-			
Lang Map %ile	.449**	.508**	-		
ITISCS	.229**	.234**	.244**	-	
Hispanic 1/0	-.201**	-.155**	-.079	-.080	-

~p<.10, *p<.05, **p<.01, ***p<.001

These estimated correlations were statistically significant at a p<.001 for math (.000) and p<.01 for reading (.006). According to the results for this sample, Hispanic student identification correlated with lower reading and math percentile performance. Interestingly, there was no statistically significant relationship between Hispanic student identification and mindset score. The non-significant Spearman estimated correlation coefficient was -.08. Therefore, according to this sample, there is no statistically significant relationship between ethnicity and mindset score. However, given the statistically significant relationship between Hispanic ethnicity and MAP performance, participant ethnicity would likely have a statistically significant impact on mindset's estimated correlation or ability to predict MAP performance. This finding supports the rejection of the second null hypothesis.

The Spearman' estimated correlations between mindset, NWEA MAP Performance, and educational program participation are presented in Table 20.

Table 20

Mindset, NWEA MAP Performance, and Educational Program Participation Estimated Correlations (Spearman's)

	Math Map %ile	Read Map %ile	Lang Map %ile	ITISCS	Gender	Special Ed	Gifted Ed	Title I Y/N(SES)
Math Map %ile	-							
Read Map %ile	.627**	-						
Lang Map %ile	.449**	.508**	-					
ITISCS	.229**	.234**	.244**	-				
Gender	-.039	.108	.151**	.050	-			
Special Ed.	-.192**	-.177**	-.220**	-.101	-.021	-		
Gifted Ed	.395**	.334**	.234**	.043	-.085	-.117*	-	
Title I Y/N (SES)	-.297**	-.278**	-.140*	.010	.013	.064	-.116*	-

~p<.10, *p<.05, **p<.01, ***p<.001

Of the four other variables, gender only had a small positive estimated correlation (.151) with the Language MAP score. This estimated correlation was statistically significant at a p value<.01 (p=.008). Therefore, in this sample, being female had a small positive estimated correlation with Language percentile performance. Special Education program participation had a small negative estimated correlation with Math (-.192), Reading (-.177), and Language (-.220) MAP performance. Math (.001), Reading (.002), and Language (.000) were all statistically significant at p values<.01. Gifted Education program participation had positive moderate estimated correlations with Math (.395) and Reading (.334) MAP performance, and a small to moderate positive estimated correlations with Language (.234) performance. These estimated correlations were all statistically significant at p values<.001. Finally, Title I program participation had moderate negative estimated correlations with Math (-.297) and Reading (-.278) MAP performance and a small negative estimated correlation with Language (-.140) MAP performance. Math and Reading estimated correlations with Title I were significant at p

values<.001 and Language and Title I estimated correlations were significant at a p value<.05 (.014).

There was no statistical significant estimated correlation between educational program participation and mindset scores. However, the estimated correlation between Special Education participation and mindset score displayed in Table 20 is worth reviewing as it approaches statistical significance at the .05 level. Given the small representation of Special Education in the sample (n=16 or 5%), it is a noteworthy finding. Special Education participation had a small negative estimated correlation (-.101) with mindset score. While this relationship was not statistically significant, the p value of this estimated correlation was .077, which is approaching statistical significance. This relationship is important to identify given the elevated frequency of the special education student's identification as fixed minded when compared to non-special education students (See Table 16).

Table 21 displays the estimated correlations between mindset, MAP subject test performance and year in school measured by grade level.

Table 21

Mindset, NWEA MAP Performance, and Year in School Estimated Correlations (Spearman's)

	Math Map %ile	Read Map %ile	Lang Map %ile	ITISCS	Grade 6	Grade 7	GRADE 8
Math Map %ile	-						
Read Map %ile	.627**	-					
Lang Map %ile	.449**	.508**	-				
ITISCS	.229**	.234**	.244**	-			
GRADE 6	-.296**	-.099	-.152**	-.172**	-		
GRADE 7	.049	.024	.095	.058	-.498**	-	
GRADE 8	.246**	.075	.056	.114*	-.498**	-.505**	-

~p<.10, *p<.05, **p<.01, ***p<.001

Sixth grade students demonstrated a small to moderate negative estimated correlation across Math (-.296), and Language (-.152) MAP performance, as well as mindset score (-.172). Math (p=.000) and Language (.008) MAP performance and mindset (.002) estimated correlations were statistically significant at a p value<.01. Being part of the 6th grade cohort predicted an overall lower Math and Language MAP score, as well as a lower mindset score. Conversely, Table 21 displays that 8th grade students demonstrated a small to moderate positive estimated correlation with Math MAP (.246) performance and mindset scores (.114). Eighth grade Math MAP performance's positive estimated correlation was statistically significant at a p value<.001 (.000) and mindset positive estimated correlations were statically significant at a p value<.05(.046). Thus, being part of the 8th grade cohort predicted an overall higher math and mindset score.

Table 22 demonstrates Spearman's estimated correlations between Dweck's identified mindset categories (Fixed, Growth, and Neutral), the continuous mindset scale: ITISCS, and MAPS subject test performance.

Table 22

Continuous vs Categorical Mindset Estimated Correlations with MAP Subject Performance

	Math Map %ile	Reading Map %ile	Language Map %ile	ITISCS	Fixed	Neutral	Growth
Math Map %ile	-						
Reading Map %ile	.627**	-					
Language Map %ile	.449**	.508**	-				
ITISCS	.229**	.234**	.244**	-			
Fixed	-.235**	-.224**	-.250**	-.788**	-		
Neutral	-.031	-.051	.036	-.193**	-.312**	-	
Growth	.238**	.243**	.198**	.868**	-.662**	-.506**	-

~p<.10, *p<.05, **p<.01, ***p<.001

Consistent with the continuous mindset measure, growth and fixed mindset categorical classifications had a small to moderate, statistically significant estimated correlation with each MAP subject performance at p<.001. Conversely, neutral mindset scores had no statistically significant relationship with MAP subject performance. Therefore, there was a small to moderate positive estimated correlation between growth mindedness and performance on MAP subject tests and a small to moderate negative estimated correlation between fixed mindedness and performance on MAP subject tests. These results support the rejection of the first null hypothesis as the Spearman's estimated correlations demonstrate there is a statistically significant relationship between mindset and MAP performance across all three MAP subject tests. These effects while small, are consistent across MAP subject tests. Furthermore, there are large Spearman's estimated correlations between ITISCS continuous scores and the categorical classifications of growth and fixed mindsets. The large Spearman's estimated

correlations between continuous ITISCS score and growth mindedness (.868) and fixed mindedness (-.788) were both statistically significant at $p<.001$. These results support the use of the ITISCS score as a continuous measure in the regression models that follow.

Bivariate correlations were estimated using Pearson's and Spearman's estimated correlation statistical procedures. All variables were examined simultaneously in one comprehensive matrix using SPSS in order to identify and evaluate all estimated correlational relationships. These variables were presented in Tables 17,18,19,20,21, and 22 in separate thematic estimated correlation matrices in order to simplify interpretation and highlight variable groupings. The estimated bivariate correlations provide evidence in support of the rejection of both null hypotheses. The evidence in support of the rejection of the first null hypothesis is based on the consistently statistically significant relationships identified in the estimated correlation matrices between mindset and MAP performance. This evidence supports a small to moderate positive relationship between a student's mindset score and MAP performance across subject tests. Higher mindset scores are consistently associated with higher MAP performance across Reading, Math, and Language subtests. The evidence in support of rejecting the second null hypothesis is based on the statistically significant relationships identified between mindset and demographic variables as well as MAP performance and demographic variables. Control variables were identified that had positive and negative impacts on student scores. The control variables that were identified with the strongest positive estimated correlations with MAP performance were GPA and gifted educational program status. Thus, those identified as being in the gifted program were more likely to have higher MAP performance scores. A higher GPA also correlated with higher MAP scores. On the

other hand, participation in special education, the Title I program (low SES), and Hispanic ethnic identity all correlated with lower MAP scores. Given these results, subgroup factors played a statistically significant role in mindset scores' ability to predict MAP performance leading to a rejection of the second null hypothesis. The preceding estimated bivariate correlation results were used as a guide in constructing the following hierarchical regression models.

Multiple Regression Models and Prototypical Plots. A series of nested hierarchical regression models were constructed for each of the NWEA MAP subject tests in order to test the two null hypotheses. Models were constructed for each of the subject tests using identical hierarchical models in order to consistently test the null hypotheses across each of the subject tests. Consistent with the results from the estimated bivariate correlation matrices, the following results from the fitted regression models support the rejection of both null hypotheses. This section contains five models constructed for each subject test as the dependent variable, Math, Reading, and Language NWEA MAP. A number of prototypical plots were constructed in order to highlight variables in the selected models that had the greatest impact on predicting NWEA MAP performance. It is important to note while interpreting the following regression models that unstandardized betas are reported in the models. The unstandardized betas represent actual percentile points on the standardized NWEA MAP tests. These unstandardized betas were selected for reporting purposes here for ease of interpretation and because they represent betas on an already standardized percentile scale (NWEA MAP, 2004).

Math, Reading, and Language hierarchical regression models demonstrated consistent results across the models and subject tests. Model 5 in each of the taxonomy

of models was chosen as the model of best fit because they represented the most accurate results for the predictor and control variables, as well as the most robust overall R squared and R squared change statistic. Controlling for gender, ethnicity, race, SES, special education participation, gifted participation, GPA, attendance, and grade level, statistically significant, unstandardized beta weights for mindset scores were identified. Across NWEA MAP subject specific models, model 5 provided consistent evidence to support the rejection of the first null hypothesis. Across Math, Reading, and Language tests, at $p<.01$, higher mindset scores were associated with higher percentile performance. Unstandardized betas representing actual percentile point performance units for Math (1.995), Reading (3.067), and Language (2.797) revealed a statistically significant positive MAP performance trend as mindset scores increased. The second null hypothesis's rejection was also supported by the consistent results across Math, Reading, and Language selected models. Selected models for each subject had a range of 3-5 statistically significant control variables, (excluding year in school) which demonstrated a statistically significant relationship among subgroup factors impacting mindsets ability to predict NWEA MAP performance. The following section explores each of the models individually and the resulting evidence which supports the rejection of both null hypotheses.

Math MAP Regression Models and Prototypical Plots. Table 23 represents the hierarchal taxonomy of five multiple regression models constructed with NWEA MAP Math subject performance as the dependent variable.

Table 23

Math MAP Percentile and ITISCS Nested Models

Predictor	Model				
	M1	M2	M3	M4	M5
Intercept	43.739	50.438	51.99	49.142	15.212
Question Predictor					
ITISCS	4.151***	3.631***	3.789***	3.382***	1.995**
Control Predictors					
Gender		-2.185	-2.563	-1.139	-3.134
Hispanic		-9.616***	-9.725***	-8.062***	-5.286**
African American		-11.971~	-8.261	-3.056	-.059
Asian		2.294	-.028	-4.660	-4.557
Pacific Islander		19.83*	17.570~	20.839*	12.765~
Native American		.743	.257	.311	-.734
Control Predictor					
SES			-21.510***	-18.518***	-19.724***
Control Predictors					
Special Education				-15.558**	-5.986
Gifted				18.823***	15.192***
Control Predictors					
GPA					9.151***
Attendance					.088
Grade 7					11.451***
Grade 8					15.701***
R^2	.052	.117	.202	.332	.510
Adjusted R^2	.049	.096	.181	.310	.486
ΔR^2	.052***	.065**	.086***	.130***	.178***
Error df (n-IV)	305	299	298	296	292
ANOVA F Statistics (all***)	16.705 (1,305)	5.651 (7,299)	9.456 (8,298)	14.717 (10, 296)	21.969 (14, 292)

~p<.10, *p<.05, **p<.01, ***p<.001

The dependent variable of NWEA MAP Math subject performance was entered into SPSS as the dependent variable and five separate models were constructed with the systematic entry of independent variables in order according to their level of question predictor status established by the literature (see Table 13). Starting with model 2, each

model contained the same question and control predictors (independent variables) as the previous model nested within it, and then introduced additional control variables. This procedure is referred to as nested hierarchical modeling because each subsequent model includes the previous model as the model raises in number culminating in the final model, which includes all variables. Only the model chosen as the model of best fit, model 5, will be reviewed in-depth here, however all statistics for each model can be reviewed in Table 23.

Model 5 was chosen as the model of best fit because it had the highest, R squared and adjusted R squared values, includes the highest number of statistically significant predictor variables, and because it controlled for variables identified in the literature as theoretically important. Prior to interpreting model 5, the ratio of cases to IVs was evaluated and multiple regression assumptions of linearity, normality, homoscedasticity and non-collinearity were checked. Results of model 5 provide evidence in support of the rejection of null hypotheses 1 and 2. Controlling for gender, ethnicity, race, SES, special education participation, gifted participation, GPA, attendance, and grade level, there was a clear, statistically significant relationship between mindset score and Math MAP performance. Furthermore, controlling for other IVs in the model, there were statistically significant subgroup factors that impacted the ability of mindset as measured by the ITISCS to predict student performance on the Math MAP assessment.

With an N of 307 and 14 independent variables, there was an average of 21.92 cases per IV, meeting the requirement according to the standard acceptable rule of thumb for this ratio (Tabachnick & Fidell, 2013). The linearity assumption was established as met through an eyeball analysis of scatterplots generated through SPSS. The normality

assumption was established as met by evaluating the histogram and P-P Plots generated through SPSS. Normality, linearity and homoscedasticity of the residuals was evaluated through evaluation of the residual plots generated in SPSS, which supported that the assumptions were met. Finally, the assumption of non-collinearity was met through evaluation of the estimated bivariate correlation matrices and collinearity statistics in the SPSS output. There was no missing data and no cases were removed as a results of the assumption testing.

Model 5 containing all 14 predictor and control variables produced an $R^2 = .510$, $F(14, 292) = 21.969$, $p < .001$. Thus, model 5's R^2 indicates that 51% of the variance in Math MAP assessment scores can be explained by the combined independent variables contained in the model. As can be seen in Table 23, mindset measured on the ITISCS had a statistically significant ($p < .01$) positive beta weight of 1.995. Thus, when controlling for gender, ethnicity, race, socioeconomic status, educational program, GPA, attendance, and grade level; higher mindset scores were associated with higher Math MAP percentile performance. According to the regression equation when controlling for the other predictors in the model, each one unit increase in mindset on the scale of 1-6 would result in an increased student's percentile score of 1.995 percentile points. Thus, a score of 6 on the ITISCS would result in a predicted increase of 11.97 (1.995 x 6) percentile points. This relationship provides significant evidence in support of the rejection of null hypothesis number 1, as there is a strong, positive statistically significant relationship between mindset score and performance on the NWEA MAP Math assessment.

Controlling for each of the included predictor variables, model 5 identified four statistically significant subgroup factors that influenced mindsets prediction of Math MAP performance. Thus, significant evidence is present for the rejection of the second null hypothesis based on the results of the following four variables; ethnicity, socioeconomic status, educational program, and GPA. Controlling for ITISCS score, gender, race, socioeconomic status, educational program, GPA, attendance, and grade level; ethnic identification as Hispanic was associated with lower predicted Math MAP percentile performance. At $p<.01$, Hispanic identified students were predicted to perform 5.286 percentile points lower on the Math MAP assessment. Similarly, lower socioeconomic status was associated with a negative impact on Math MAP performance. Controlling for ITISCS scores, gender, ethnicity, race, educational program, GPA, attendance, and grade level; socioeconomic status measured by participation in the Title I program predicted that a student would score 19.724 percentile points lower on the Math MAP assessment (at $p<.001$). Conversely, student participation in the gifted educational program was associated with higher performance on the Math MAP assessment. Controlling for ITISCS scores, gender, ethnicity, race, socioeconomic status, special education program participation, GPA, attendance, and grade level; gifted program participation is associated with higher Math MAP percentile performance. At $p<.001$, students participating in the gifted program were predicted to perform 15.192 points higher on the Math MAP assessment than those not participating in the gifted program. GPA was the final variable that was identified in model 5 as having a statistically significant impact on Math MAP performance. Controlling for ITISCS scores, gender, ethnicity, race, socioeconomic status, special education program participation, gifted

program participation, attendance, and grade level, GPA was positively associated with higher Math MAP percentile performance. At $p<.001$, students were predicted to perform 9.151 percentile points higher on the Math MAP assessment per unit of GPA.

Results from model 5 clearly support the rejection of both null hypotheses. In order to more clearly demonstrate these findings, some of the variables' impact have been highlighted in the prototypical plots that follow (Figure 1 & Figure 2). The two variables that will be highlighted below are ethnicity and socioeconomic status. In order to illustrate the impact of these variables, the regression equation was entered into Excel in order to produce prototypical plots based on the model 5 equation. Table 24 shows the generic regression equation, the regression equation with specified variables, and provides a variable key.

Table 24

Math Map Model 5 Regression Equation

Generic Equation:

$$Y=15.212+(1.995*X1)+(-3.134* X2)+(-5.286*X3)+(-.059*X4)+(-4.557* X5)+(12.765* X6)+(-.734* X7)+(-19.724* X8)+(-5.986 X9)+(15.192* X10)+ (9.151* X11)+(.088* X12) + (11.451 X13)+15.701* X14)$$

Solved for Equation in Excel:

$$Y=15.212+(1.995*1-6)+(-3.134*1)+(-5.286*1)+(-0.059*0)+(-4.557*0)+(12.765*0)+ (-0.734*0)+(-19.724*0/1)+(-5.986*0)+(15.192*0)+(9.151*3.2722)+ (0.088*7.5251) +(11.451*1)+(15.701*0)$$

Variable Labels:

X1=ITISCS, X2=gender, X3=Ethnicity, X4=African American, X5=Asian, X6=Pacific Islander, X7=Native American, X8=SES, X9=SPED, X10=Gifted, X11=GPA, X12=Absences, X13=Grade 7, X14=Grade 8

Figure 1 graphs the estimated regression equation in Table 24 generated in Excel for Hispanic and non-Hispanic students across possible mindset scores on the ITISCS solved for a student with the remaining variables set at the following: female student,

Caucasian, non-gifted, non-special education, non-Title I, 7th grader with the mean GPA (3.27), and the average number of periods absent (7.5).

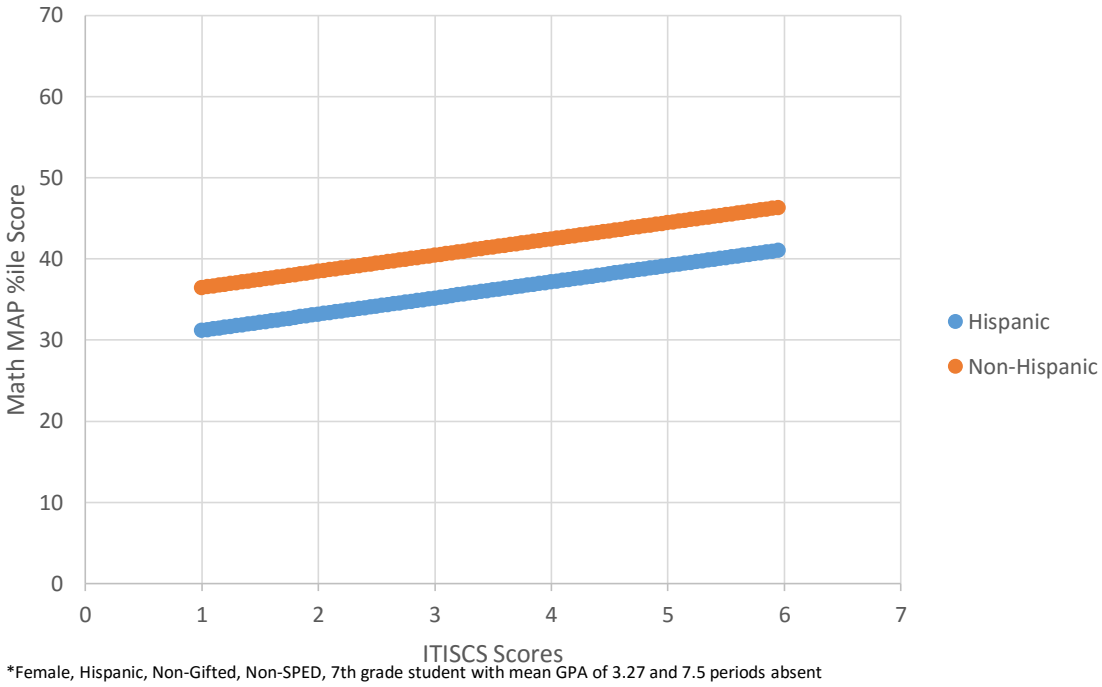

Figure 1. Impact of being Hispanic on math percentile scores across possible ITISC scores*.

Figure 1 demonstrates that across possible mindsets as measured by the ITISCS, there was a persistent achievement gap on the Math MAP assessment between those that identified as Hispanic and non-Hispanic. Mindset's ability to predict Math MAP performance was significantly mediated by a student's ethnicity, supporting the rejection of the second null hypothesis.

According to the results of model 5, a student's socioeconomic status also significantly impacted mindset's ability to predict student performance on the Math MAP assessment as demonstrated in Figure 2. Figure 2 graphs the regression equation in Table 24 generated in Excel for Title I and non-Title I students across possible mindset scores

on the ITISCS solved for students with the remaining variables set at the following: female, non-Hispanic, Caucasian student, non-gifted, non-special education, in 7th grade with the mean GPA (3.27), and the average number of periods absent (7.5). Figure 2 demonstrates that there was a significant achievement gap between Title I and non-Title I students across all possible mindset scores on the ITISCS. This persistent achievement regardless of mindset scores supports the rejection of the second null hypothesis because Title I subgroup identification did have a statistically significant impact at a large effect size on mindset's ability to predict Math MAP performance.

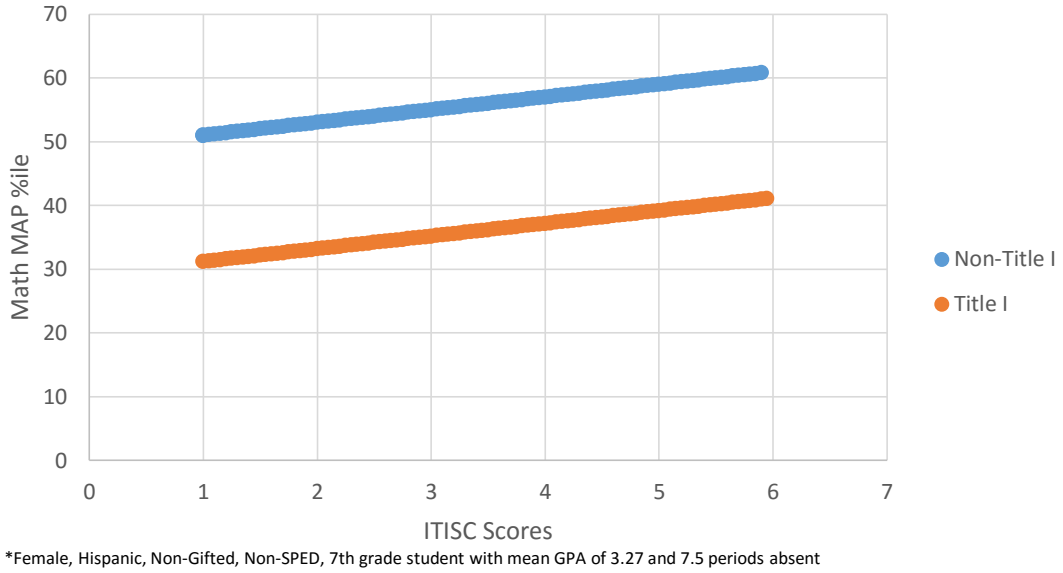

Figure 2. Impact of Title I status on math MAP percentile scores* across possible ITISC scores.

The nested taxonomy of regression models developed for Math MAP performance and the highlighted variables in the prototypical plots support the rejection of both null hypotheses. There was evidence of a statistically significant relationship between mindset scores on the ITISCS and student performance on the NWEA Math MAP assessment and this relationship was mediated by a statistically significant

relationship between Math MAP performance and subgroup identification. Model 5 was chosen as the model of best fit to describe these relationships.

Reading MAP Regression Models and Prototypical Plots. Table 25 represents the hierarchal taxonomy of 5 multiple regression models constructed with NWEA MAP Reading subject performance as the dependent variable. NWEA MAP Reading subject performance was entered into SPSS as the dependent variable and 5 separate models were constructed with the systematic entry of independent variables according to their level of question predictor status established by the literature (see Table 13). Starting with model 2, each model contained the same question and control predictors (independent variables) as the previous model nested within it, and then introduced additional control variables. Only the model chosen as the model of best fit, model 5, will be reviewed in-depth here, however all statistics for each model can be reviewed in Table 25.

Table 25

Reading MAP Percentile and ITISCS Nested Models

Predictor	Model				
	M1	M2	M3	M4	M5
Intercept	51.245***	52.591***	54.178***	52.817***	11.794~
Question Predictor					
ITISCS	4.452***	3.989***	4.150***	3.692***	3.067**
Control Predictors					
Gender		4.175	4.431~	5.530*	1.53
Hispanic		-4.652~	-4.762~	-3.358	-.580
African American		-13.245~	-9.477	-4.338	2.880
Asian		.953	-1.405	-5.507	-.895
Pacific Islander		16.44	14.147	16.362~	10.808
Native American		-1.209	-1.702	-1.719	-2.266
Control Predictor					
SES			-21.852***	-19.147***	-15.286***
Control Predictors					
Special Education				-21.031***	-11.363*
Gifted				14.223***	10.178***
Control Predictors					
GPA					12.257***
Attendance					.252*
Grade 7					3.663
Grade 8					3.144
R^2	.056	.093	.175	.283	.414
Adjusted R^2	.053	.071	.153	.258	.386
ΔR^2	.056***	.037~	.083***	.107***	.132***
Error df (n-IV)	305	299	298	296	292
ANOVA F	18.046	4.359	7.915	11.659	14.746
*Statistics (all***)*	(1,305)	(7,299)	(8,298)	(10,296)	(14,292)

~p<.10, *p<.05, **p<.01, ***p<.001

Model 5 was chosen as the model of best fit because it had the highest, R squared and adjusted R squared values, included the highest number of statistically significant predictor variables, and because it controlled for variables identified in the literature as theoretically important. Prior to interpreting model 5, the ratio of cases to independent variables was evaluated and multiple regression assumptions of linearity, normality,

homoscedasticity and non-collinearity were checked. Results of model 5 provide evidence in support of the rejection of null hypotheses 1 and 2. There was a clear, statistically significant relationship between mindset score and Reading MAP performance and there were statistically significant subgroup factors that impact the ability of mindset as measured by the ITISCS to predict student performance on the Reading MAP assessment.

With an N of 307 and 14 independent variables, there was an average of 21.92 cases per IV, meeting the requirement according to the standard acceptable rule of thumb for this ratio (Tabachnick & Fidell, 2013). The linearity assumption was established as met through an eyeball analysis of the scatterplots generated through SPSS. The normality assumption was established as met by evaluating the histogram and P-P Plots generated through SPSS. Normality, linearity and homoscedasticity of the residuals was evaluated through evaluation of the residual plots generated in SPSS, which supported that the assumptions were met. Finally, the assumption of non-collinearity was met through evaluation of the estimated bivariate correlation matrices and collinearity statistics in the SPSS output. There were no missing data and no cases were removed as a results of the assumption testing.

Model 5 containing all 14 predictor and control variables produced an $R^2 = .414$, $F(14, 292) = 14.746, p < .001$. Thus, given model 5's R^2 results, 41.4% of the variance in Reading MAP assessment performance was explained by the combined independent variables contained in the model. As can be seen in Table 25, mindset measured on the ITISCS had a statistically significant ($p < .01$) positive beta weight of 3.067. Thus, when controlling for gender, ethnicity, race, socioeconomic status, educational program, GPA,

attendance, and grade level, higher mindset scores were associated with higher Reading MAP percentile performance. According to the regression equation, when controlling for the other predictor variables, each one unit increase in mindset on the scale of 1-6 resulted in an increased student's percentile score of 3.067 percentile points. Thus, a score of 6 on the ITISCS would result in a predicted increase of 18.402 (3.067 x 6) percentile points. This relationship provides significant evidence in support of the rejection of null hypothesis number 1, as there was a strong, positive statistically significant relationship between mindset score and performance on the NWEA MAP Reading assessment.

Model 5 results represented in Table 25 identified five statistically significant subgroup factors that impacted mindset's prediction of Reading MAP performance. Thus, significant evidence is present for the rejection of the 2nd null hypothesis based on the results of the following four variables; socioeconomic status, special education program participation, gifted education program participation, GPA, and number of absences. Controlling for ITISCS score, gender, ethnicity, race, educational program, GPA, attendance, and grade level, socioeconomic status measured by Title I program participation was associated with lower Reading MAP percentile performance. At $p<.01$, Title I program identified students were predicted to perform 15.286 percentile points lower on the Reading MAP assessment. Similarly, special education program participation was associated with a negative impact on Reading MAP performance. Controlling for ITISCS scores, gender, ethnicity, race, gifted educational program, Title I program, GPA, attendance, and grade level; special education program participation predicted that a student would score 11.363 percentile points lower on the Reading MAP

assessment at $p<.05$. Conversely, student participation in the gifted educational program was associated with higher performance on the Reading MAP assessment. Controlling for ITISCS scores, gender, ethnicity, race, socioeconomic status, special education program participation, GPA, attendance, and grade level, gifted program participation was associated with higher Reading MAP percentile performance. At $p<.001$, students were predicted to perform 10.178 percentile points higher on the Reading MAP assessment than those that were not participants in the gifted program. Controlling for ITISCS scores, gender, ethnicity, race, socioeconomic status, special education program participation, gifted program participation, attendance, and grade level, GPA was also identified in model 5 to have a statistically significant positive impact on Reading Map performance. At $p<.001$, students were predicted to perform 12.257 percentile points higher on the Reading MAP assessment per unit of GPA. Finally, controlling for ITISCS scores, gender, ethnicity, race, socioeconomic status, special education program participation, gifted participation, GPA, and grade level, higher absentee rates as measured by periods missed were found in this model to be associated with higher reading scores. However, according to the school administration, there was a consistent pattern of high performing students struggling with attendance due to diagnoses of anxiety, which may be responsible for these findings.

Results of model 5 clearly support the rejection of both null hypotheses. In order to more clearly demonstrate these findings, some of the variables' impact have been highlighted in the prototypical plots that follow. The three variables that are highlighted below are special education program participation, gifted education program participation, and socioeconomic status. In order to illustrate the impact of these variables, the

regression equation was entered into Excel in order to produce prototypical plots based on the model 5 equation. Table 26 shows the generic regression equation, the regression equation with specified variables, and provides a variable key.

Table 26

Reading MAP Model 5 Regression Equation

Generic Equation:

$Y=11.794+(3.067*X_1)+(1.532 * X_2)+(-.580 *X_3)+(2.880 *X_4)+(-.895 * X_5)+(10.808* X_6)+(-2.266* X_7)+(-15.286* X_8)+(-11.363 X_9)+(10.178* X_{10})+(12.257* X_{11})+(.252* X_{12})+(3.663 X_{13})+3.144* X_{14})$

Solved for Equation in Excel:

Y=11.794+(3.067*1-6)+(1.532 * 1)+(-.580 *1)+(2.880 *0)+(-.895 * 0)+(10.808* 0)+(-2.266* 0)+(-15.286* 1/0)+(-11.363 *0)+(10.178* 0)+(12.257* 3.2722)+(.252*7.5251)+(3.663*1)+3.144* 0)

Variable Labels:

X1=ITISCS, X2=gender, X3=Ethnicity, X4=African American, X5=Asian, X6=Pacific Islander, X7=Native American, X8=SES, X9=SPED, X10=Gifted, X11=GPA, X12=Absences, X13=Grade 7, X14=Grade 8

Similar to the findings of the Math MAP model 5, Reading MAP Model 5 identified a number of subgroup factors with statistically significant relationships that impacted mindset's ability to predict performance on the Reading MAP assessment. Title I status, Special Education program participation, gifted program participation are highlighted below in Figures 3, 4, and 5 respectively.

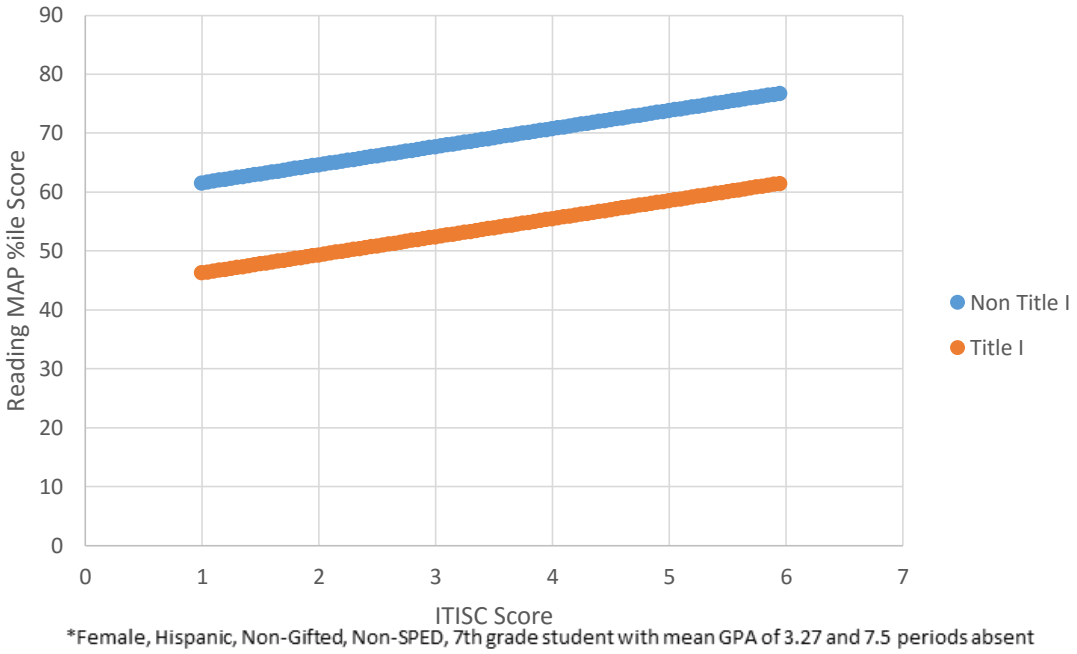

Figure 3. Impact of Title I Status on Reading Map Percentile Scores* Across Possible ITISCS Scores

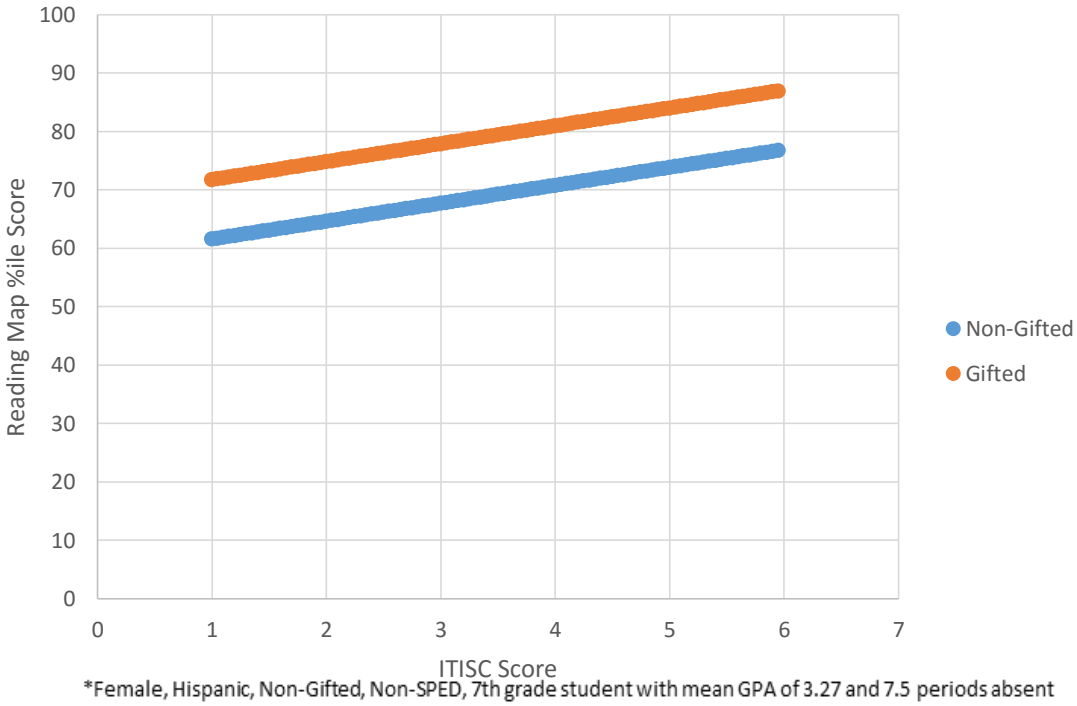

Figure 4. Impact of Gifted Program Identification on Reading Percentile Scores* Across Possible ITISC Scores

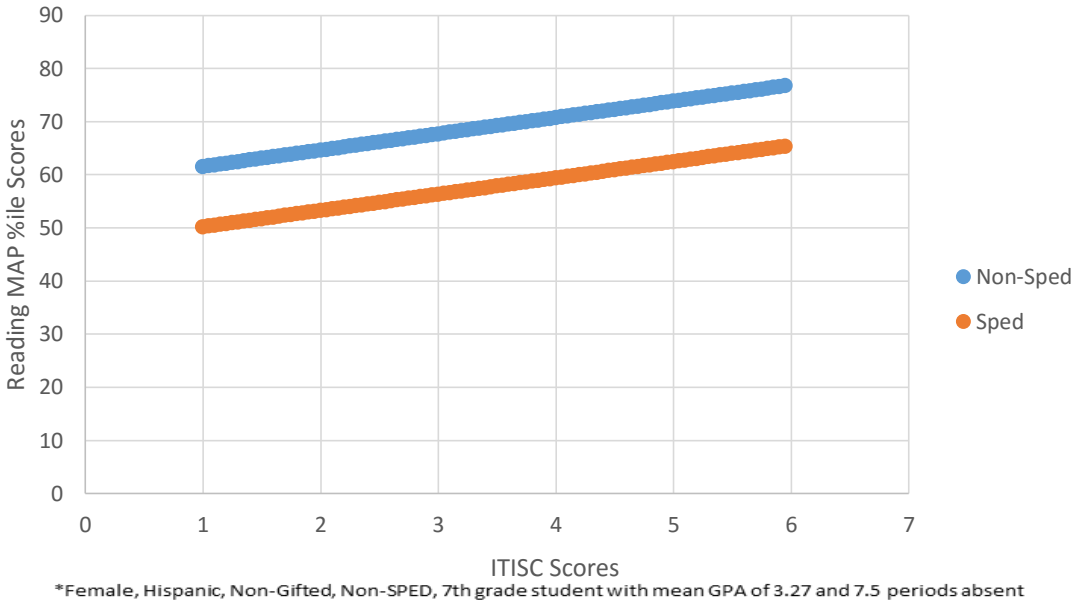

Figure 5. Impact of Special Education Program Identification on Reading MAP Percentile Scores* Across Possible ITISCS Scores

Language MAP Regression Models and Prototypical Plots. Table 27 presents the hierarchal taxonomy of five multiple regression models constructed with NWEA MAP Language subject performance as the dependent variable. The dependent variable of NWEA MAP Language subject performance was entered into SPSS as the dependent variable and 5 separate models were constructed with the systematic entry of independent variables entered in order according to their level of question predictor status established by the literature (see Table 13). Starting with model 2, each model contained the same question and control predictors (independent variables) as the previous model nested within it, and then introduced additional control variables. Only the model chosen as the model of best fit, model 5, will be reviewed in-depth here, however all statistics for each model can be reviewed in Table 27.

Model 5 was chosen as the model of best fit because it had the highest, R squared and adjusted R squared values, included the highest number of statistically significant

predictor variables, and because it controlled for variables identified in the literature as theoretically important. Prior to interpreting model 5, the ratio of cases to IVs was evaluated and multiple regression assumptions of linearity, normality, homoscedasticity and non-collinearity were checked. Results from model 5 provide evidence in support of the rejection of null hypotheses 1 and 2. There was a clear, statistically significant relationship between mindset score and Language MAP performance and there were statistically significant subgroup factors that impacted the ability of mindset as measured by the ITISCS to predict student performance on the Language MAP assessment.

Table 27

Language MAP Percentile and ITISCS Nested Models

Predictor	Model				
	M1	M2	M3	M4	M5
Intercept	49.983***	50.085***	50.806***	50.544***	23.018**
Question Predictor					
ITISCS	4.349***	3.900***	3.973***	3.542***	2.797**
Control Predictors					
Gender		4.657~	4.774*	5.531*	2.770
Hispanic		-3.222	-3.273	-2.209	-.142
African American		-8.300	-6.587	-2.147	1.901
Asian		3.297	2.224	-1.025	1.404
Pacific Islander		9.146	8.103	9.382*	5.269
Native American		2.394	2.170	2.112	1.475
Control Predictor					
SES			-9.933*	-7.751*	-5.874
Control Predictors					
Special Education				-21.721***	-14.952**
Gifted				10.178**	7.483**
Control Predictors					
GPA					8.236***
Attendance					.058
Grade 7					7.041*
Grade 8					3.996
R^2	.059	.091	.110	.198	.280
Adjusted R^2	.056	.069	.086	.171	.245
ΔR^2	.059***	.031	.019*	.089***	.081***
Error df (n-IV)	305	299	298	296	292
ANOVA F	19.288	4.256	4.589	7.323	8.099
*Statistics (all***)*	(1,305)	7,299)	(8,298)	(10,296)	14,292)

~p<.10, *p<.05, **p<.01, ***p<.001

With an N of 307 and 14 independent variables, there was an average of 21.92 cases per IV, meeting the requirement according to the standard acceptable rule of thumb for this ratio (Tabachnick & Fidell, 2013). The linearity assumption was established as met through an eyeball analysis of the scatterplot generated through SPSS. The

normality assumption was established as met by evaluating the histogram and P-P Plots generated through SPSS. Normality, linearity and homoscedasticity of the residuals were assessed through evaluation of the residual plots generated in SPSS which supported that the assumptions were met. Finally, the assumption of non-collinearity was met through evaluation of the estimated bivariate correlation matrices and collinearity statistics in the SPSS output. There were no missing data and no cases were removed as a result of the assumption testing.

Model 5 containing all 14 predictor and control variables produced an $R^2 = .280$, $F(14, 292) = 8.099$, $p < .001$. Thus, model 5's R^2 indicated that 28% of the variance in Language MAP assessment performance was explained by the combined independent variables contained in the model. As can be seen in Table 27, mindset measured on the ITISCS had a statistically significant ($p < .01$) positive beta weight of 2.797. Thus, when controlling for gender, ethnicity, race, socioeconomic status, educational program, GPA, attendance, and grade level, higher mindset scores were associated with higher Language MAP percentile performance. According to the regression equation, each unit increase in mindset on the scale of 1-6 resulted in an increased student's percentile score of 2.797 percentile points. Thus, a score of 6 on the ITISCS would result in a predicted increase of 16.782 (2.797 x 6) percentile points. This relationship provides significant evidence in support of the rejection of null hypothesis number 1, as there was a strong, positive statistically significant relationship between mindset score and performance on the NWEA MAP Language assessment.

Model 5 includes three statistically significant subgroup factors that impacted mindsets prediction of Language MAP performance. Thus, significant evidence is

present for the rejection of the 2nd null hypothesis based on the results of the following three variables; special education program participation, gifted education program participation, and GPA. Controlling for ITISCS score, gender, ethnicity, race, socioeconomic status, gifted education program participation, GPA, attendance, and grade level, special education program participation was associated with lower Language MAP percentile performance. At $p<.01$, special education program participants were predicted to perform 14.952 percentile points lower on the Language MAP assessment. Conversely, controlling for ITISCS scores, gender, ethnicity, race, socioeconomic status, special education program participation, GPA, attendance, and grade level, gifted program participation was associated with higher Language MAP percentile performance. At $p<.01$, students in the gifted program were predicted to perform 7.483 percentile points higher on the Language MAP assessment than those that were not participants in the gifted program. Controlling for ITISCS score, gender, ethnicity, race, socioeconomic status, special education participation, gifted education program participation, attendance, and grade level, GPA was also identified in model 5 to have a statistically significant positive impact on Language Map performance. At $p<.001$, students were predicted to perform 8.236 percentile points higher on the Language MAP assessment per unit of GPA.

Results of model 5 clearly support the rejection of both null hypotheses. In order to more clearly demonstrate these findings, impact of special education program participation has been highlighted in the prototypical plots that follow (Figure 6). In order to illustrate the impact of these variables, the regression equation was entered into Excel in order to produce prototypical plots based on the model 5 equation. Table 28 shows the

generic regression equation, the regression equation with specified variables, and provides a variable key.

Table 28

Language MAP Model 5 Regression Equation

Generic Equation:

$Y=23.018+(2.797*X_1)+(2.770 * X_2)+(-.142 *X_3)+(1.901 *X_4)+(1.404 * X_5)+(5.269* X_6)+(1.475 * X_7)+(-5.874* X_8)+(-14.952 X_9)+(7.483* X_{10})+(8.236* X_{11})+(.058* X_{12})+(7.041*X_{13})+(3.996* X_{14})$

Solved for Equation in Excel:

Y=23.018+(2.797*1-6)+(2.770 * 1)+(-.142 *1)+(1.901 *0)+(1.404 * 0)+(5.269* 0)+(1.475 * 0)+(-5.874 * 1/2)+(-14.952*0)+(7.483*0)+(8.236* 3.2722)+(.058* 7.5251)+(7.041*1)+(3.996* 0)

Variable Labels:

X1=ITISCS, X2=gender, X3=Ethnicity, X4=African American, X5=Asian, X6=Pacific Islander, X7=Native American, X8=SES, X9=SPED, X10=Gifted, X11=GPA, X12=Absences, X13=Grade 7, X14=Grade 8

In order to highlight the role special education program participation had on mediating mindset's ability to predict student performance on the Language MAP assessment, Figure 6 was developed.

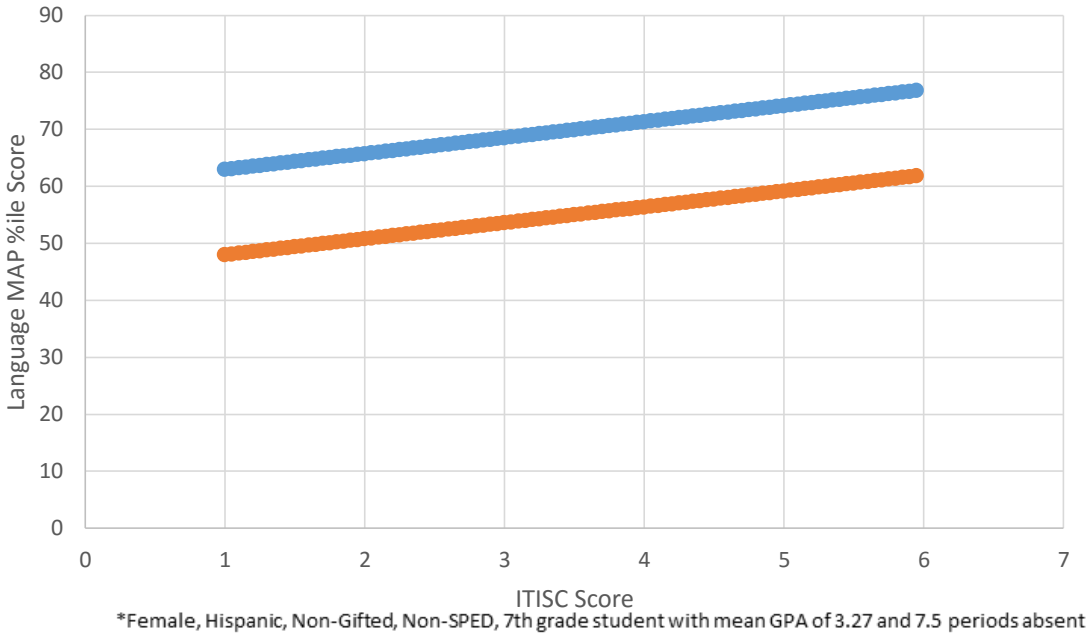

Figure 6. Impact of Special Education Status on Language Percentile Scores* Across ITISCS Scores

Results Conclusion

The findings of the statistical procedures conducted in this study provide clear evidence for the rejection of both null hypotheses. The first null hypothesis was rejected because a consistent statistically significant relationship was found between mindset scores measured by the ITISCS and performance on the NWEA MAP assessments across Math, Reading, and Language subject tests. The total possible predicted impact for the highest mindset score on the ITISCS on student MAP performance (the difference between a score of 1 and 6 on the ITISCS) measured in percentile points when controlling for the other independent variables in the model was substantial (Math=11.97, Reading=18.402, and Language=16.782). The second null hypothesis was rejected because consistent, statistically significant relationships were found across MAP subject tests where subgroup factors mediated mindset score's ability to predict MAP performance. The primary subgroup factors that were found to mediate mindset's ability

to predict MAP performance were Hispanic ethnicity (negative impact: Math), socioeconomic status (negative impact: Math and Reading), special education participation (negative impact: Reading and Language), gifted education participation (positive impact: Math, Reading, and Language), and GPA (positive impact: Math, Reading, and Language). As demonstrated here, there was a clear relationship between mindset and NWEA performance, which was mediated by subgroup factors.

Chapter V: Discussion

This chapter will discuss the findings of the study in order to respond to the stated research question and contextualize the results. These questions will be responded to with an overview of the findings, their connection to the theory described in the literature, the potential limitations of the study, suggestions for further research, and finally implications for practitioners.

The research question for this study was: What is the relationship between mindset (entity vs. incremental beliefs) and student performance on the Northwest Evaluation Association's (NWEA) Measure of Academic Progress (MAP)*?* The sub-questions of this study were; 1) What is the relationship between mindset (entity vs. incremental beliefs) and student performance on the Northwest Evaluation Association's (NWEA) Measure of Academic Progress (MAP)? and 2) What is the relationship between subgroup factors (demographics, academic program, academic achievement measure by GPA, and time spent on the assessment) and mindset's ability to predict student performance on the NWEA MAP?

Overall, the findings of this study support the rejection of the null hypotheses. The study found that mindset scores correlated with standardized test performance and that subgroup factors mediated this relationship. The findings in this study both confirm the research that has been done in connecting mindset to academic achievement outcomes and extends the understanding of this relationship to include student performance on standardized tests. While it has been established that student mindsets can predict academic achievement (Blackwell et al., 2007; Dweck et al., 1995; Yeager, Walton, et al., 2013), the evidence in support of a similar relationship between mindset scores and standardized test achievement has been limited. In addition to contributing to the

understanding of the impact of mindset scores on standardized tests, this study also highlights important subgroup factors that, controlling for mindset scores, have strong relationships with test performance.

This study demonstrates that student mindset has a consistent measurable relationship with student NWEA MAP performance. The researcher obtained student assessment data for three separate subject test administrations (tests were given over the course of 3 weeks) of the NWEA MAP subject tests in math, reading, and language. When these results were compared to student mindsets through estimated bivariate correlation tables and multiple regression analysis, a statistically significant relationship was consistently identified. When measured in percentile points, controlling for gender, ethnicity, race, SES, special education program participation, gifted education program participation, GPA, attendance, and grade level, students who scored a 1(*lowest*) compared to those scoring a 6 (*highest*) score on the mindset measure were predicted to differ by 12 (Math), 18 (Reading), and 17 (Language) percentile points. Given the documented manipulability of mindsets through interventions (Blackwell et al., 2007; Yeager, Paunesku, et al., 2013) and the documented ability to deliver these interventions at scale efficiently (Paunesku, 2013; Yeager, Walton, et al., 2013), these findings represent a clear path forward for increasing student performance on standardized tests. Through the evaluation of subgroup traits this study also helps to identify groups of students who may benefit most from interventions.

Beyond establishing a link between student mindsets and standardized test performance, this study also helps identify those who would most benefit from these interventions. While the link between mindset and test performance was consistent

across subject tests, subgroup factors that mediated mindset's ability to predict standardized test performance varied by subject test. According to the results of this study, depending on the subject test, specific groups were identified as performing better or worse when controlling for mindset. For example on the math subject test, Hispanic students performed (controlling for the measured independent variables including mindset) 5 percentile points lower than non-Hispanic students. Students of lower SES (controlling for the measured independent variables including mindset) were predicted to score 20 percentile points lower than their higher SES counterparts. Gifted students on the other hand (controlling for the measured independent variables including mindset) were predicted to score an average of 15 percentile points higher on the math subject test. The reading test yielded similar results. Students of lower SES background and special education participants (controlling for the measured independent variables including mindset) scored 15 and 11 percentile points lower than their higher SES and non-Special Education counterparts. Consistent with math subject test performance, students identified as gifted (controlling for all other independent variables including mindset) were predicted to score 10 percentile points higher than their non-gifted peers. Finally, the language subject test (controlling for the measured independent variables including mindset) revealed that special education students were predicted to score 15 percentile points lower than their non-special education peers while gifted students were predicted to perform 7 percentile points higher than non-gifted students.

The consistency of these results across subject tests support the validity of the findings. The three separate administrations of the NWEA MAP subject tests over a period of 3 weeks and their consistent estimated correlation with mindset scores supports

the predictive validity of the mindset score. These findings provide evidence that mindset scores have a consistent relationship with standardized test performance on the NWEA MAP across subject tests. Furthermore, the impact of subgroup factors on test performance provides guidance as to which groups of students would benefit the most from mindset interventions. These findings are consistent with existing literature, while also increasing the understanding of the relationship between mindset and standardized test scores and the subgroup factors that influence this relationship.

Consideration of the Findings in the Context of Current Research

This study is a small part of a broader trend in educational research that has increased attention and the allocation of research resources toward the study of non-cognitive traits and their role in student achievement (Gutman & Schoon, 2013). This trend seeks to broaden cold cognitive models to include the role of emotion and motivation in academic achievement (Shell et al., 2010). To date, the empirical evidence that has been collected regarding the role of mindset in student achievement has established mindset as one of the dominant motivational constructs in the educational research literature (Renaud-Dubé et al., 2015).

Mindset's role in student academic achievement has been well documented (Blackwell et al., 2007; Dweck, 2007; Dweck & Legget, 1988; Paunesku, 2013; Paunesku et al. 2015; Romero, Paunesku, & Dweck, 2011; Yeager & Walton, 2011; Yeager, Walton et al., 2013). This study sought to further the understanding of the role of mindsets in a specific area of academic achievement, namely the relationship between standardized test performance and mindset.

The findings of this study both confirm and challenge existing literature. Duckworth et al., (2012), suggested that motivational constructs correlate higher with

GPA than with standardized test performance. This study found the opposite. As shown in Table 17, mindset scores on the ITISCS were found to correlate with GPA at only .167 ($p<.01$) while mindset scores correlated with Math, Reading, and Language scores each to a higher degree at a lower p value (.228, .236, and .244 respectively at $p<.001$). This study also challenges the findings of Holmlund and Silva (2009) who found that non-cognitive skills did not correlate with higher test performance. They found that non-cognitive interventions, including those targeting motivation did not have an impact on standardized test performance. The current study, while not establishing a causal link, found evidence that mindset does in fact correlate with higher standardized tests scores. The findings of the current study are consistent with the findings that mindset can improve test performance, especially for minority students (Aronson, et al. 2002; Dweck, 2007; Good et al., 2003; Good et al., 2007). Overall, this study supports the results of other studies that have found mindset and motivation to correlate positively with standardized test performance (Dvorak, 2014; Liu et al., 2012; Murayama et al., 2013).

This study found that, while mindset scores on the ITISCS consistently contributed to predicting student achievement across sub-groups, the traits and factors of these sub-groups impacted mindset's ability to predict standardized test performance. Specifically, while students within a sub-group had different predicted test performance levels based on their mindset scores, these sub-groups differed significantly from each other. This study confirmed some of the existing literature regarding sub-group traits and challenges other findings.

Previous studies have found that mindset's ability to predict achievement, particularly in the area of math, is mediated by gender (Dar-Nimrod & Heine, 2006;

Dweck, 2000; Grant & Dweck, 2003). The current study did not find this relationship. Specifically, gender did not correlate to a statistically significant degree with math performance, reading performance, or ITISCS mindset scores. As shown in Table 20, there was only a small estimated correlation between language performance and gender (.151 at $p<.01$). Gender beta weights also lacked statistical significance across Math, Reading, and Language multiple regression models. However, it is important to note here that this may be due to the specific nature of the population studied (higher achieving students) as female underachievement in math, which is a consistent finding in the literature was not present in this sample.

Three consistent themes from the literature regarding sub-group factors that were confirmed in this study were the underperformance of Hispanic students, low SES students, and special education students. Consistent with the literature, students identified as Hispanic and those students eligible for the Title I program (a measure of SES) were predicted to perform consistently below their peers (Blackwell et al., 2007; Dar-Nimrod & Heine, 2006; Dvorak, 2014; Grant & Dweck, 2003; O'Rourke et al., 2014). This achievement gap consistently found in the literature was also represented in this sample providing validity evidence as these results establish consistency with evidence based on relation to other variables. These results should inform the systematic monitoring and intervention of students' academic achievement. Also consistent with the literature, special education students were found to have a higher prevalence of fixed mindedness (Baird et al., 2009). Table 16 shows that 62.5% of the special education students in the sample had ITISCS results in the fixed minded range while only 27% of non-special education students were identified as fixed minded. Given these findings,

mindset interventions should be considered when designing individual education plans for students in special education. Finally, this study also confirmed the findings of Ziegler and Stoeger (2010), that mindset equally impacts the performance of students who are identified as gifted and non-gifted. Given that the stability of giftedness over the course of a student's career has been shown to be limited (Bronson & Merryman, 2009), it is important that students identified as gifted are not excluded from mindset interventions and monitoring.

In closing, the results of this study contribute to the understanding of the role a student's mindset plays in researchers' abilities to predict standardized test performance. Overall, this study confirms previous findings regarding mindset's role in predicting student achievement and the impact of subgroup factors. However, it is important that given the specific sample used in this study, the results should not be over generalized. Specific guidance on limitations of this study's results can be found in the following sections.

Limitations of the Study

There are two primary limitations of this study that inhibit the generalizability of the results. First, this study was correlational in design, thus predictive conclusions are limited. Secondly, the sample chosen, while of ample size to conduct the statistical analyses, was in many ways unique to the school where the study was conducted and should be strictly evaluated before generalizing results. The nuances of these limitations will be reviewed here and should be used as a guide for generalization of results and replication of the study.

According to Vogt (2007), there are three main criteria when assessing causation. These are; Y must precede X, X and Y must covary, and other possible causes must be ruled out. In the variable language of this study, in order to demonstrate causation that mindset scores result in NWEA MAP performance, these three criteria would need to be satisfied. First, it would need to be established that the mindset preceded the NWEA MAP performance. This criterion was not met as this was a cross-sectional correlational study where the data were gathered during the same period of time. Second, mindset and NWEA MAP performance would need to be seen to covary. This criterion was met according to the results of the estimated bivariate correlation procedure and the multiple regression analyses. Finally, other possible causes for NWEA MAP performance would need to be ruled out. This criterion was partially met as there were a number of control variables included in the multiple regression analyses that isolated the effect of mindset on NWEA MAP performance. Given Vogt's criteria, a major limitation of the results of this study is that causation was not established, thus limiting the generalizability of the results.

Perhaps more important than the failure to establish a causal link between mindset score and NWEA MAP performance, is the fact that the sample of students in this study represents a potentially unique population and therefore generalization of these results may only be applicable to environments with similar profiles. According to Tabachnick and Fidell (2013), generalization of research findings is limited by the degree to which the sample represents the overall population of interest. Specifically, this population was defined by voluntary participation in the lottery to enter the college preparatory charter school, its demographics were not representative of the region, and its academic

achievement was well above the local and national averages. This can be attributed to the purposive nature of the sample and the researcher's interest in investigating the high achieving charter school's population. According to Fraenkel and Wallen (2009), the sample in this study can best be described as a purposive sample as there was a specific population of interest and the study does not purport to be generalizable to all students. First, the students in the school, despite being randomly selected by the lottery or achieving enrollment due to a sibling preference, have all self-selected their enrollment in the school lottery (student or parent). The school studied is a public charter school with no geographic boundaries, or criteria beyond sibling preference. Thus, all students enrolled are enrolled as an alternate choice to their local public school to which they would have otherwise been assigned. Second, the student demographics do not have a similar profile to the general population of the metro area within which the charter school is located. The school has fewer students who identify as Hispanic, has a larger portion of its population that identifies as Caucasian, and has less than one quarter the number of students who qualify for Title I support when compared to the local metropolitan school system as a whole. Finally, the average academic achievement of the students was significantly higher than the local and national averages. For example, student mean NWEA MAP scores for Math (59.81 percentile), Reading (68.49 percentile), and Language (66.82 percentile) demonstrated that the students' performed consistently well above the national average. Given the self-selected nature of the school's population, its lack of representative demographics, and its above average academic performance, the generalizability of results is limited.

In conclusion, the primary limitation of this study is the limited generalizability of the study results. Due to the correlational design, a causal claim between mindset scores and NWEA MAP performance could not be established. Furthermore, the unique nature of the charter population studied can be described as a purposive sample, which should serve as a warning to those attempting to generalize the results beyond schools with similar profiles.

Recommendations for Further Research

While the findings of this study are compelling, the next steps in the research process should be primarily guided by this study's limitations. Specifically, the next step that should be taken in order to continue the line of inquiry of this study should be to design a randomized, experimental study, which would attempt to establish a causal link between mindset and NWEA MAP assessment performance in a sample population that would be generalizable. Beyond the sample, additional research should also be conducted using other standardized test measures.

Further research should seek to evaluate if these effects can be identified across numerous standardized testing formats. It is important to note that the NWEA MAP assessment is a computer adaptive test (CAT). As a CAT, the test questions are constantly adjusting based on the student's previous answer. If the student answers correctly, the questions become more difficult. If the student answers incorrectly, the questions become easier. This particular CAT is also untimed. The specific characteristics of the NWEA MAP assessment may make it uniquely sensitive to student motivation and mindsets in particular. Further research is required to evaluate whether or not results similar to this study would be found on standardized assessments that are not computer adaptive and are limited by time parameters.

Implications for Professional Practice

Educational practitioners can use these findings in conjunction with the published literature to justify a classroom, school, and district level emphasis on cultivating a growth mindset in students. The development of a growth mindset should be seen as most important in at risk student populations. Groups identified in this study as at risk for poor test performance include Hispanic students, low SES students, and special education students. Growth mindset interventions should be a part of a comprehensive approach to supporting the performance of at risk students.

There are two practical paths for school districts to take when seeking to include mindset interventions as part of a comprehensive strategy to improve student achievement. First, teachers should be properly trained on the benefits of cultivating a growth mindset in students and on classroom based intervention strategies that support mindset development in students (Dweck, 2016). Second, districts should investigate the deployment of online, standardized mindset intervention strategies. These strategies have been shown to impact student mindsets and resulting achievement in as few as two, 45 minute sessions (Paunesku et al., 2015).

The most sustainable approach to incorporating mindset interventions into professional practice is to imbed them in already established structures and activities. For example, if schools are already practicing the Professional Learning Community (PLC) approach to teacher collaboration, mindset should be imbedded in this approach. PLCs have as an essential agreement that all students can learn and emphasizes systematically evaluating the reasons for the lack of student's progress. Mindset theory can be woven into this practice, allowing for a common theoretical framework as to why students can all learn and how to evaluate their lack of progress in a productive way. PLCs are only

one example of widespread existing school practices which are compatible with an emphasis on mindset theory. School and district leaders should identify the current practices in their own environment and work to incorporate mindset theory into those practices that are already successful.

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Appendix A

ITISC: *Implicit Theories of Intelligence Scale for Children-Self Form (Dweck, 2000)*

This questionnaire has been designed to investigate ideas about intelligence. There are no right or wrong answers. We are interested in your ideas. Using the scale below, please indicate the extent to which you agree or disagree with each of the following statements by writing the number that corresponds to your opinion in the space next to each statement.

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

*___1. You have a certain amount of intelligence, and you really can't do much to change it.

*___2. Your intelligence is something about you that you can't change very much.

*___3. You can learn new things, but you can't really change your basic intelligence.

___4. No matter who you are, you can change your intelligence a lot.

___5. You can always greatly change how intelligent you are.

___6. No matter how much intelligence you have, you can always change it quite a bit.

*These items can you be used alone.

Note: For studies of how people's theories of intelligence affect they judge and teat others, use the "Others" form of the theories of intelligence scales. The "Others" form is constructed by replacing the word "you" with the words "people," "someone," or "everyone" (as in the "kind of person" scale below).

Appendix B

Col #	Variable Name	Variable Description	Variable Metric
1	HISP	Hispanic Ethnicity	0=No 1=Yes
2	REID	Racial identification	1=White 2=Black 3=Asian or Pacific Islander 4=American Indian or Alaskan Native
3	GEN	Gender	Female=0 Male=1
4	GPA	Grade point average at quarter	1= ≦ 1.49 2=1.5-1.99 3=2.0-2.49 4=2.5-2.99 5=3.0-3.49 6=3.5-4.0+
5	ATTEN	School attendance at quarter measured by number of missed days	Number of days missed
6	EDPRO	Educational Program	1=General Education 2=Gifted Education 3=Non-gifted Special Education
7	SES	Socioeconomic Status as measured by title one program participation	0=Not Title I Eligible 1=Title I Eligible
8	YINSCH	Year in school	1=6th

			2=7th 3=8th
9	*ITISC*	Total score on Implicit Theories of Intelligence Scale for Children	Range: 1-6 1-2=Fixed Minded 5-6=Growth Minded 3-4=Neutral
10	*MMAP*	Math: Measure of Academic Progress Percentile	Percentile score reported by grade level: Percentile Range: 1^{st}-99^{th}
11	RMAP	Reading: Measure of Academic Progress Percentile	Percentile score reported by grade level: Percentile Range: 1^{st}-99^{th}
12	LMAP	Language: Measure of Academic Progress Percentile	Averaged percentile between math and reading Range:1^{st}-99th