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Mindsets, Attitudes, and Achievement in Undergraduate Statistics Courses

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Abstract
The purpose of this study was to determine the effects of theories of intelligence and an intervention of incremental mindset training on students' attitudes toward statistics and their mastery of content in an introductory statistics college course. The sample was 547 undergraduate students at a small, faith-based, liberal arts college in the Midwest.

A pretest-posttest design was used for the three instruments implemented. The Comprehensive Assessment of Outcomes in a first Statistics course (CAOS) assessed students' statistical literacy. The Student Attitudes Towards Statistics – 36© (SATS©) assessed six components of students' attitudes toward statistics including affect, cognitive competence, difficulty, effort, interest, and value. The Theories of Math Intelligence Scale – Self Form (TMIS) assessed students' mindsets toward mathematics. Students in the treatment group received four brief incremental mindset training sessions throughout the semester. The initial mindset categorization had no significant effect on the difference in mean SATS© or CAOS gain ($p < .05$); the power to detect a difference was limited due to a low response rate.

Students in the treatment group decreased at a rate greater than students in the control for the component of effort on the posttest SATS© assessment when the pretest was controlled for, $F(1, 138) = 14.778$, $MSE = 10.954$, $p < .001$. The remaining components produced no significant differences between groups ($p < .05$). Students in the control group also improved more on their mastery of statistics as assessed by the posttest CAOS when the pretest CAOS was controlled for, $F(1, 297) = 6.796$, $MSE = .100$, $p = .010$.

Analysis revealed that females gained more than males in the treatment group on the SATS© component of value, $\mu Diff = 0.829$, $t(28)= 3.123$, $p = .004$. The remaining components of the SATS© assessment did not produce statistically significant results ($p < .05$).

Recommendations for practice include creating classrooms that support growth mindsets and the design of mindset training. Recommendations for research include replication of the current research in statistics and other mathematics courses. A final recommendation calls for an examination of the differences by gender on the SATS© assessment.

Keywords
statistics course, college students, teaching, statistical literacy, Comprehensive Assessment of Outcomes (CAOS), Student Attitudes Towards Statistics – 36© (SATS©), Theories of Math Intelligence Scale – Self Form (TMIS), mindset training

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Comments
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- Dr. Kevin Reins, Committee Chairperson

MINDSETS, ATTITUDES, AND ACHIEVEMENT IN UNDERGRADUATE STATISTICS COURSES

By

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ABSTRACT

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The University of South Dakota, 2015

Dissertation directed by Kevin Reins

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This abstract of approximately 350 words is approved as to form and content. I recommend its publication.

Signed Kevin J. Reins

Dr. Kevin Reins

DOCTORAL COMMITTEE

The members of the committee appointed to examine the dissertation submitted by Valorie L. Zonnefeld find it satisfactory and recommend that it be approved.

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CHAPTER 1

Introduction

Many factors affect students' mathematics achievement, including their view of intelligence. Carol Dweck (2006) has identified two implicit theories of knowledge: incremental and entity. Incremental theorists believe that intelligence is malleable and can be increased with effort (Bruning, Schraw, & Norby, 2011). Entity theorists view intelligence as unchangeable (Dweck & Leggett, 1988). Effort cannot influence intelligence in an entity mindset since intelligence is fixed. When faced with academic challenges, individuals with incremental mindsets respond with behaviors that promote mastery, while those with entity mindsets respond with negative behaviors (Dweck & Leggett, 1988). Additionally, Mangels, Butterfield, Lamb, and Dweck (2006) found that individuals classified with incremental mindsets tended to endorse mastery learning goals while entity theorists strongly endorsed performance goals which demonstrate competence. These mindsets play an important role in academic persistence and achievement which are both imperative in college success (Good, Rattan, & Dweck, 2012).

Nationally, less than two-thirds of students who enroll in four-year colleges graduate. When community colleges are included, the graduation rate drops to 53% (Porter, 2013). College administrators, policy makers, and educators have explored many possible reasons for this low graduation rate including weak freshman integration programs, academic preparation, socioeconomic background, and motivation to learn (Pang, 2010).

A common roadblock on many students' path to graduation is successfully completing a college-level mathematics course (Topper, 2011). One large university in the United States reported that 40% of students enrolled in introductory, college-level mathematics courses dropped out, with another 10% receiving failing grades (Kim & Kellert, 2010). Successfully completing a college-level math course is a momentum point that is "very strongly correlated with postsecondary achievement" (Leinbach & Jenkins, 2008, p. 20). Similar situations across the country have given introductory mathematics courses the title 'gatekeeper to achieving a college degree' (Bryk & Treisman, 2010). Bryk and Treisman (2010) argue, "math should be a **gateway**, not a gatekeeper, to a successful college education" (p. 1).

A commonly required mathematics course in many undergraduate programs is introductory statistics (Ruggeri, 2011). Statistics is a unique type of mathematics course that combines quantitative skills with analysis. As a result of the need for analytical skills in a diverse set of professions, the number of students required to take statistics has rapidly increased in the past half century making statistics the most common subject across disciplines (Ruggeri, 2011). Statistics has morphed from a course taught to "a narrow group of future scientists in agriculture and biology, to being a family of courses, taught to students at many levels, from pre-high school to post-baccalaureate, with very diverse interests and goals" (Aliaga et al., 2005, p. 7). According to the Conference Board of the Mathematical Sciences, the fall 2010 enrollment in elementary statistics courses at four-year colleges in the United States was 56% higher than fall 2005 and has more than doubled since the fall 1995 semester (Blair, Kirkman, & Maxwell, 2013). Cobb (2007) asserted that all colleges have experienced a boom in statistics course enrollments as increasing number of students and employers recognize the need for statistical literacy.

As a mathematics course, statistics creates an obstacle for undergraduates, as many students experience anxiety and negative attitudes toward the subject (Evans, 2007; Ruggeri, 2011; Ruggeri, Dempster, Hanna, & Cleary, 2008). As student diversity has increased in introductory statistics courses, so have the challenges. “Today’s teachers face challenges of motivation and exposition that are substantially greater than those of half a century ago” (Aliaga et al., 2005, p. 7). With the increase in diversity of undergraduate majors, students may not see the relevance of statistics in their lives, contributing to the struggle for motivation (Kim & Kellert, 2010).

One response to poor performance in introductory mathematics courses and low undergraduate retention rates is increasing the academic entrance requirements for students; however, ability is not the sole predictor of success (Lucio, Rapp-Paglicci, & Rowe, 2011). Educators recognize that students of similar abilities often achieve at vastly different levels. Every fall, “a surprising number of seemingly bright high school graduates unexpectedly fail to adapt to their new university achievement setting” (p. 1946) while students with less ability blossom (Boese, Stewart, Perry, & Hamm, 2013). Cognitive learning theory may give insight into the disparity seen between students’ achievements and their ability levels.

Cognitive learning theory focuses on the effects of underlying thought processes on the learner. Students do more than gain knowledge and master skills while learning; they also simultaneously build beliefs about their ability to be successful learners (Boekaerts, Otten, & Voeten, 2003). Implicit theories of intelligence is an area of cognitive learning theory concerned with individuals' view of knowledge and its attainment. This mental construct of a student's view of knowledge influences her behavior regarding academics. Two students with different patterns of metacognition may both value intelligence, but employ different strategies in order to reach their goals (Dweck & Leggett, 1988). The underlying thought processes of students and patterns of thinking are mental constructs that are often referred to as mindsets (Dweck, 1999).

Using Dweck's theoretical framework regarding mindsets, entity theorists hold fixed mindsets and see their environments and abilities as set with little that can be done to alter them (Dweck & Leggett, 1988). In contrast, incremental theorists hold a growth mindset and believe that intelligence can be developed. This belief in growth changes their view of people, institutions, and the environment since all have the ability to improve (Dweck & Leggett, 1988).

Mindsets are most powerful when facing challenge and responding to failure (Dweck, 1999). Failure is painful in a growth mindset, but it does not define the individuals since they view it as a learning experience (Dweck, 2006). While students with both entity and incremental mindsets may place blame for a failure on the same source, one difference is that entity theorists will view the cause of the failure as uncontrollable while an incremental theorist views it as controllable (Dweck & Leggett, 1988). Belief of lack of control over a failure creates more cognitive distress for an entity theorist (Dweck, 1999) which often leads him or her to respond with negative behaviors including blaming, lying, and avoiding challenge (Dweck, 2006). These causal attributions affect an individual's reactions to failure and success, but more importantly, they influence one's expectations for future achievements (Boekaerts et al., 2003).

A study of students at the University of Hong Kong demonstrated negative, fixed-mindset responses. All classes at this prestigious Chinese university are conducted in English (Dweck, 2006). When new students were presented with their English proficiency scores and offered a chance to improve their skills, only those who believed that intelligence was malleable showed interest. The students' concern about appearing deficient caused those with fixed mindsets to not take advantage of an opportunity to improve their English skills. Dweck (2006) concluded that students with fixed mindsets are so concerned with appearing smart, that they act dumb.

In contrast to students with fixed mindsets, students who hold growth mindsets exert more effort to reach their goals. A study of pre-medicine students in an organic chemistry course measured students' mindsets. Students with incremental mindsets reported higher intrinsic motivation, deeper processing of concepts, greater increases in grades throughout the course, and after controlling for SAT scores, higher grades (Grant & Dweck, 2003). Mangels, Butterfield, Lamb, and Dweck (2006) observed the brain wave activity of students using electroencephalography (EEG) and noticed that students with incremental mindsets who tended toward challenging situations found negative feedback less threatening (Mangels et al., 2006). It is this ability to expend effort and confront negative feedback that makes a growth mindset so powerful in an educational setting (Dweck & Leggett, 1988).

Attribution theory is an area of study in cognitive learning theory that is a forerunner to Dweck's theories of intelligence. The theoretical framework developed by Bernard Weiner is similar to mindset theory as it deals with the causal explanations that individuals attach to success and failure (Syed, 2013). Attribution theory is consistent with Bandura's (1997) social cognitive theory "which posits that the interpretation students make of their past successes and failures serve as an important source of information about their efficacy" (Usher, 2009, p. 307).

A key difference between attribution theory and the study of mindsets is that attributions focus on previous events while mindset theory has a forward-looking focus. "Most people display what is known as a self-serving bias, and will attribute their successes to internal factors (such as being intelligent or hard-working) and their failures to external factors (such as poorly-worded questions)" (Banks & Woolfson, 2008, p. 49). Unfortunately, these "false attributions can easily discourage a student's motivation" (p. 131) and subsequently influence his or her behavior in future events (Robertson, 2000). In response to Weiner's groundbreaking work, educational researchers developed attribution training, "a process that involves improving a person's beliefs in the causes of his or her own failures and successes to promote future motivation for achievement" (Robertson, 2000, p. 111). Attribution training has been shown to successfully improve academic success in numerous studies (Boese et al., 2013; Shores & Smith, 2010).

Following the developmental pattern of attribution theory, educators and researchers have developed numerous treatments to foster a growth mindset including emails, videos, and worksheets intended to help students understand the malleability of intelligence and the importance of effort (Dooms, 2013; Kamins & Dweck, 1999; Kim & Kellert, 2010; Roads to Success, 2010; Sriram, 2010). Some teachers have also attempted pedagogical changes in an effort to support growth mindsets including changes to the testing environment, lessons on how the brain acquires knowledge, and changes in the source of teacher praise. The most notable example of mindset training is the

Brainology curriculum designed by Mindset Works Inc. (2008). Brainology consists of computer modules created for use with fifth- through ninth-grade students that educate students on the brain's role in learning and the power of a growth mindset. In research of middle school students, Donohoe, Topping, and Hannah (2012) found that the Brainology curriculum significantly increased students' tendency toward incremental mindsets.

Incremental mindset training has received a lot of attention from both educators and psychologists in recent decades. "A considerable body of research is emerging from top cognitive psychology and cognitive neuroscience labs demonstrating that fundamental aspects of intelligence, and even intelligence itself, can be altered through training" (Dweck, 2008, p. 1). Evidence is mounting that "what a *student* thinks about intelligence can have a powerful effect on his or her achievement (Aronson, Fried, & Good, 2002, p. 115). In their examination of eighth-grade students during mathematics tests, Ryan, Ryan, Arbuthnot, and Samuels (2007) found that student's beliefs and goals influenced their performance. Of particular note are studies demonstrating that students' mindsets can be altered (Aronson et al., 2002; Cutts, 2008; Dweck, 2008; Good, Aronson, & Inzlicht, 2003; Kim & Kellert, 2010).

Theories of intelligence play an important role in mathematics classes as well since there is evidence that mindsets are domain specific (Dweck, 2008). Research has shown that "students who believe that intelligence or math and science ability is simply a fixed trait (a fixed mindset) are at a significant disadvantage compared to students who believe that their abilities can be developed (a growth mindset)" (Dweck, 2008, p. 1). Incremental mindset training also affects motivation in mathematics classes. In a study of seventh-grade students, teachers, who were blind to treatment, chose three times as many students in the growth treatment group as showing marked improvement in their motivation compared to those in the control (Blackwell, Trzesniewski, & Dweck, 2007).

Students' attitudes toward mathematics are an important aspect of achievement. A positive relationship has been shown between student attitudes toward mathematics and their achievement in mathematics courses (Aiken, 1970; Evans, 2007; Nolan, Beran, & Hecker, 2012). In a study of email messages to undergraduates students, Kim and Kellert (2010) found that the participants' attitudes decreased over the semester, with the exception of the students who received belief change strategy emails with personal messages (Kim & Kellert, 2010). The belief change strategy emails were personalized to each student and addressed students' beliefs about their ability to learn and the speed at which they learn.

One aspect of attitudes toward statistics is the anxiety that students hold toward the subject. Onwuegbuzie (2003) theorized that the anxiety that students experience toward statistics reduces the efficiency of the memory and its utilization for approaching statistics and statistical problems. More research is needed to understand the role of attitudes toward statistics and their effect on student performance and achievement.

While research has been conducted on mathematical mindsets concerning students' belief in their ability to learn mathematics, no research is available on the impact of mathematical mindset in introductory statistics courses. Based on the findings of these initial studies of incremental mindset training in mathematics classes, the focus of this research was on the effects of entity and incremental mindsets on mastery of statistical content and attitudes toward statistics. The effects of training in an incremental mindset also were examined for mastery of statistical content and attitudes towards statistics.

Statement of the Problem

This research examined the effects of mindset and an intervention of incremental mindset training in an introductory statistics college course on student attitudes toward statistics and student mastery of statistical content.

Research Questions

Five research questions were explored in this study:

1. What differences exist in students' attitudes toward statistics based on their initial mindset toward mathematics?
2. What differences exist in students' attitudes toward statistics between those who did and did not receive incremental mindset training?
3. What differences exist in students' acquisition of statistical knowledge between those who did and did not receive incremental mindset training?
4. What differences exist between students' initial mathematical mindset and their change in statistical knowledge throughout an introductory statistics course?
5. What differences exist by gender in the change in students' attitudes toward statistics for students who received training in an incremental mindset?

Significance of the Study

Pang (2010) suggested that improving students' experiences in mathematics courses will increase the retention of many aspiring college graduates. Statistics is a unique mathematics course that is required for many undergraduate students and the number of students who take statistics continues to grow (Onwuegbuzie & Wilson, 2003). The fall 2010 enrollment in undergraduate, elementary statistics courses in the United States reached 81,000 students (Kirkman & Stangl, 2012). This is a 50% increase from 2005 and a 65% increase from 1995. Given that statistics is a ‘problem subject’ for many students, an examination of possible methods to support students is valuable and timely (Cook, 2010; Onwuegbuzie & Wilson, 2003).

Simultaneous to the growth in statistics, research on implicit theories of knowledge has expanded. Unfortunately, only a handful of studies have examined how to create a growth mindset in the mathematics classroom (Kim & Kellert, 2010). This research answers the call from Dweck (2008) to “study ways in which the education environment can teach and support a growth mindset over time” (p. 2). Shores and Smith (2010) have called for future research specifically in mathematics education to focus on developing strategies to improve students’ implicit theories of knowledge with the goal of helping students develop strategies to cope with failure.

Recent decades “have seen an extraordinary level of activity focused on how students learn statistics” (Aliaga et al., 2005, p. 8). Unfortunately, given the growth of research in both mindset and statistics education, a paucity of research exists connecting mindsets, attitudes, and achievement in statistics courses. Results of this study add to the knowledge base of implicit theories of knowledge and support continuous improvement in undergraduate statistics pedagogy.

Definition of Key Terms

Key terms that will be frequently used throughout the research are defined to ensure clear communication. The researcher has developed any definition that are not cited.

Affect: A component of attitude as measured by the Student Attitudes Towards Statistics© (SATS) instrument concerning student's feelings toward statistics (Schau, 2003).

Attribution: A belief that an individual holds regarding the cause of one's failures and successes; attributions occur after an event, but can affect future actions (Weiner, 1985).

Attribution Training: Activities used to improve an individual's beliefs concerning the causes of their failures or successes to improve future motivation for achievement (Robertson, 2000).

Cognitive Competence: A component of the SATS© instrument concerning students confidence in their knowledge and ability to perform statistics (Schau, 2003).

Cognitive Learning Theory: An approach to examining learning that emphasizes the underlying thought processes of the learner.

Contingent Self-Worth: A mental construct in which an individual's self-worth is tied to his or her success or failure in a specific domain (Niiya, Brook, & Crocker, 2010).

Difficulty: A component of the SATS© instrument concerning students' perception of the level of challenge that statistics provides as a subject (Schau, 2003).

Effort: A component of the SATS© instrument concerning the amount of effort a student exerts to master statistics (Schau, 2003).

Entity or Fixed Mindset: A mindset based on the belief that basic qualities and abilities are static and unchangeable; in this research entity mindsets refer to beliefs that intelligence and the ability to change it are set (Dweck, 2006).

Implicit Theories of Intelligence: Metacognitive processes an individual holds concerning beliefs about their cognitive abilities (Mangels et al., 2006).

Incremental or Growth Mindset: A mindset based on the belief that basic qualities and abilities can be cultivated through effort; in this research incremental mindsets refer to beliefs that intelligence and the ability to alter it are changeable (Dweck, 2006).

Intelligence: The measure of an individual’s knowledge or skills (Dweck, 2000).

Interest: A component of attitude as measured by the SATS© instrument concerning student’s personal interest in statistics (Schau, 2003).

Mastery Goal: A goal that an individual holds to increase competence (Dweck & Leggett, 1988).

Mindset: A perception that shapes an individual’s view of the nature of intelligence and knowledge acquisition (Dweck, 2006).

Motivation: An individual’s inclination to fully participate and persevere in a learning task (Syed, 2013).

Performance Goal: A goal that an individual holds to demonstrate competence to oneself or others (Dweck & Leggett, 1988).

Plasticity: A description of the brain's ability to grow and create new connections when exercised (Dweck, 2008).

Reform-Based Statistics Curricula: Introductory statistics curricula which introduce inference early in the semester through simulation-based methods (Tintle et al., 2014).

Self-Efficacy: Domain-specific beliefs that an individual holds about their abilities and potential for future success (Bandura, 1999).

Self-Esteem: The evaluation and acceptance that an individual has concerning their worth (McLeod, 2008).

Self-Handicap: A behavior that individuals participate when they are uncertain of their ability to perform that harms performance such as procrastinating or withholding effort (Niiya et al., 2010).

Self-Regulation: Essential skills that individuals use when tasks are long, complex, or unpleasant (Dweck, 1999).

Statistics Attitude: For this study, statistics attitude refers to an individual's affect, cognitive competence, value, perception of difficulty, interest, and effort toward statistics as measured by the SATS© instrument (Schau, 2003).

Statistical Knowledge: In this study, statistical knowledge is defined as statistical literacy, conceptual understanding, and reasoning about variability (Assessment Resource Tools for Improving Statistical Thinking, 2005).

Stereotype Threat: The burden that an individual feels to confirm cultural stereotypes which limit their academic abilities and achievement (Grant & Dweck, 2003).

Student: In this study, a student is an individual enrolled in an undergraduate introductory college statistics course.

Traditional Statistics Curricula: Introductory statistics curricula which use theory-based approaches, typically beginning with descriptive statistics, followed by probability and sampling distributions, concluding with statistical inference (Tintle, VanderStoep, Holmes, Quisenberry, & Swanson, 2011).

Value: A component of the SATS© instrument which assesses a student's beliefs regarding the utility, relevance, and importance of statistics both personally and professionally (Schau, 2003).

Limitations and Delimitations of the Study

Every study is accompanied by limitations and delimitations. In this study, several factors affected the generalizability and validity of the results. One limitation to the generalizability was the statistics curriculum implemented by the college. All course sections used a reform-based statistics curriculum which was under development. The curriculum utilized simulation-based methods which introduced inference earlier in the semester. This curriculum was in its final stages of development and was not expected to be a factor in the study. This new curriculum covered the same topics as a typical statistics curriculum, but approached them in an alternative sequence with an emphasis on conceptual understanding.

Another limitation of this study concerned the control group. Students in the treatment group received four 15-minute incremental mindset training sessions. Students in the control group, however, did not receive equivalent training by an outside person.

This limitation affected research questions two and three which used the control group for comparison purposes.

An additional concern of the control group was a curricular change in the introductory statistics course between the control and the treatment groups. Students in the fall 2011 through spring 2014 semesters took the class for three credit hours, while students in the treatment group took the class in its four credit hour version. This was not expected to be a significant limitation since the concepts taught in both conditions remained the same. The four-credit version of the course used for the treatment added the use of a statistical software package and an application project.

The quasi-experimental design of this study was a limitation since it only allowed for conclusions of association, not causation. A delimitation of the sample was that it was comprised of students from one college who enrolled in a specific statistics course. This limits the generalizability of the findings.

An additional limitation of this research was the role of the environment. There is evidence that the educator affects the learning, attitude, and even mindset of students in their class (Cutts, 2008; Dweck, 2008). The professor for the treatment classes was debriefed on the study, theories of intelligence, and the role of the teacher in fostering incremental mindsets in an effort to create a supportive classroom environment. Despite this debriefing, the instructor in the treatment group also represented a change from the instructors in the control group. Previous semesters were taught by tenure-track professors and the treatment group was taught by an adjunct instructor. It is unknown how these changes may have affected the results. The final environmental influence was stereotype threat. It is not possible to control for stereotype threat, although the professor was debriefed on stereotype threat and made an effort to create a safe learning environment.

A significant limitation of the current study was an administrative error made during the posttest portion of the research which may have had a negative impact on the sample size. It was discovered during a response rate check that the student invitation to complete the posttest SATS© and CAOS had not been sent. Thus, students were invited to complete the posttest assessments on the first day of exams. Students were then given four days to complete the posttest SATS© and CAOS, instead of the originally planned seven days similar to the control group. The small sample size for the treatment group inhibited data analysis which limited the power to detect small effects for research questions one, four, and five.

Organization of the Study

The study is organized into five chapters. The first chapter provides a background to the issue under study, research questions, and the significance of the study. Chapter 2 is a review of literature in the field of implicit theories of knowledge and attitudes toward mathematics. Chapter 3 outlines the methodology to be utilized in this research. Chapter 4 shares the results of the study and accompanying statistical analysis and Chapter 5 concludes the research with a summary, discussion, conclusions, and recommendations.

CHAPTER 2

Review of Related Literature and Research

Relevant research and literature are reviewed in this chapter to provide a setting and background for the study of implicit theories of knowledge in introductory statistics classes. Due to the plethora of resources available on implicit theories of knowledge and on mathematics education, an exhaustive review of the literature is not plausible. Following Maxwell's (2006) guidelines for literature reviews, the review focuses on resources that are most relevant to this study. The literature review follows in sections beginning with the landscape of statistics education and an overview of cognitive learning theory. Attribution theory is examined prior to mindset theory. Examples of attribution and incremental mindset training are considered, as well as studies that examine the relationship between mindset and the environment. Throughout the review, research on the application of these theories to mathematics teaching and learning at the college and K-12 levels are interwoven. Chapter 2 closes with an examination of critiques of mindset theory.

Statistics Education

Introductory statistics courses have experienced changes and challenges over the past century. The increase in enrollment and diversification of students required to take statistics at the undergraduate level will be examined as well as alterations to the traditional statistics curriculum. The section closes with an examination of challenges that many students and instructors face in statistics courses.

Changes. Introductory statistics courses are growing and changing rapidly. Despite the large number of students that take statistics courses at the undergraduate level, the course is a relatively new requirement for many college programs. In 1925, R. A. Fischer published the first statistics textbook that was written for practicing scientists (Aliaga et al., 2005). The 1961 release of a text by Mosteller, Rourke, and Thomas helped statistics enter disciplines outside of the sciences (Aliaga et al., 2005). In 1978, the release of two textbooks "marked the birth of what we regard as the modern introductory statistics course" (Aliaga et al., 2005, p. 7). Given the relative youth of introductory statistics courses for students outside of traditional fields that emphasize quantitative literacy, there is much to be learned about effective practice and pedagogy.

In recent decades, there has been an increased focus on statistics pedagogy (Kesici, Baloğlu, & Deniz, 2011). One area that has received attention is the development of instruments to gain information about students, including their attitudes and mastery of material in statistics. Numerous instruments have been developed over the past half century to assess students' attitudes towards statistics including the Statistics Course Attitude Scale in 1954, the Statistics Attitude Scale (SAS) in 1980, the Attitudes Toward Statistics Scale (ATS) in 1985, and the SATS© questionnaire in 2003 (Nolan et al., 2012). Only the SAS, ATS, and SATS© have demonstrated significant evidence of validity and reliability.

The SATS© questionnaire was developed by Schau (2003) to learn more about students' attitudes at the beginning and end of a statistics course, and to further research on students' attitudes in statistics classes. The original 28-item instrument was expanded to 36 items which validly measures six components of attitude. Schau's instrument has been used in other studies of statistics including Bond, Perkins, and Ramirez (2012), Chiesi and Primi (2010), Coetzee and van der Merwe (2010), Harpe, Phipps, and Alowayesh (2012), and Swanson, Vander Stoep, and Tintle (2014).

Another area of interest for educators and researchers was the knowledge that students gained in statistics courses. The Statistical Reasoning Assessment (SRA) was published in 1998 as one of the first instruments developed to give insight into the statistical reasoning of high school students (Tempelaar, 2004). The SRA is unique in its attempt to provide an "easily scorable instrument that captures students' thinking, reasoning, and application of knowledge" (Garfield, 2003, p. 23).

At the undergraduate level, the Assessment Resource Tools for Improving Statistical Thinking (2005), also known as ARTIST, created the Comprehensive Assessment of Outcomes in a first Statistics course (CAOS) instrument which can be given both at the beginning and at the end of the semester. The purpose of the CAOS instrument is to learn more about undergraduate students' statistical literacy and reasoning with a focus on their conceptual understanding of the subject. The CAOS instrument has been used in other studies of statistics including Hannigan, Gill, and Leavy (2013), Slauson (2008), Tintle and colleagues (2014; 2011), and Zieffler (2007).

Another aspect of the increased focus on the pedagogy of statistics was the role of the American Statistical Association. In 2003, the association created a task force with a mandate to produce Guidelines for Assessment and Instruction in Statistics Education. These guidelines are summarized in the following recommendations:

1. Emphasize statistical literacy and develop statistical thinking
2. Use real data
3. Stress conceptual understanding, rather than mere knowledge of procedures

4. Foster active learning in the classroom
5. Use technology for developing conceptual understanding and analyzing data
6. Use assessments to improve and evaluate student learning (Aliaga et al., 2005, pp. 14-21).

The impetus for these changes was the availability of technology that allowed students to focus on the concepts, and not the computation, of statistics.

Cobb followed this report in 2007 with a landmark article calling for a reimagining of the traditional statistics curriculum. He claimed that statistics education as a profession "stands at the threshold of a fundamental reshaping of how we do what we do, how we think about what we do, and how we present what we do to students who want to learn about the science of data" (p. 1). The crux of Cobb's (2007) argument for change also rests on the rapid increase in available computing power. He claimed that what has traditionally been taught was shaped by what was computable. This restriction no longer holds with today's easy access to computing power. Cobb promoted the idea of a randomized-based curriculum that focused on inference, as opposed to the traditional distribution centered methods which blur the connection between the model and reality.

One curriculum that has answered Cobb's call is currently under development by Tintle, Chance, et al. (2011), and will soon be published by John Wiley & Sons. Initial class testing of this reform curriculum has shown positive results. The CAOS instrument was administered both before and after the new curriculum was taught, and showed that students learned significantly more about statistical inference than students using a traditional curriculum while maintaining comparable understanding on most other concepts (Tintle, VanderStoep, et al., 2011). A retest of students' retention four months after the course also showed increased retention of concepts emphasized in the reform curriculum compared to students using the traditional curriculum (Tintle, Topliff, VanderStoep, Holmes, & Swanson, 2012). Increases in the enrollment and diversity of students in introductory statistics along with reforms to the traditional curriculum are all factors which affect the current research.

Challenges. Multiple challenges exist for students in introductory statistics classes. Lalonde and Gardner (1993) researched the three common challenges of anxiety, attitude, and ability to predict successful completion of introductory statistics courses. They concluded that the difficulty associated with learning statistics is similar to that of acquiring a foreign language.

Anxiety and negative attitudes are challenges for many students and consequently their statistics professors as well (Chiesi & Primi, 2010; Evans, 2007; Kesici et al., 2011; McGrath, 2014; Onwuegbuzie & Wilson, 2003; Ruggeri, Dempster, et al., 2008). The sources of student anxiety and attitudes are varied and have an influence on the statistics classroom. Kesici et al. (2011) researched undergraduate students in statistics courses in Turkey and noted that the highest sources of anxiety for students concerned the class itself and tests. Additionally, Bandalos, Yates, and Thorndike-Christ (1995) noticed a negative relationship between students' efficacy and their anxiety about statistics.

Student attitudes play an important factor in academic achievement (Evans, 2007). Chiesi and Primi (2010) examined undergraduate students enrolled in introductory statistics for their attitudes both before and after the semester using the SATS© instrument. They found that students' attitudes at the beginning of the semester were related to their achievement at the end of the course. An additional relationship was found where students' attitudes at the beginning of the semester were directly related to their mathematical knowledge. This creates a challenge for many instructors since students enter introductory statistics with a wide variety of mathematical backgrounds.

Another challenge for students and instructors is the increased diversity of student majors enrolled in introductory statistics. Many students from programs with qualitative backgrounds such as education and psychology do not see the connections between statistics and their intended careers (Chiesi & Primi, 2010; Kim & Kellert, 2010; Onwuegbuzie & Wilson, 2003; Ruggeri, Dempster, et al., 2008). This lack of perceived relevance can cause students to have a negative experience in introductory statistics courses.

An additional challenge of the increased diversity of students enrolled in introductory statistics is the broader range of students' mathematical abilities and preparations. As more students outside of the sciences enroll in introductory statistics courses, the mathematical ability of students is diversified and, consequently, increased the number of students with poor preparation or weak mathematical skills.

A lack of connection, along with attitudes, anxiety, and ability, are among the challenges that many students and professors face in undergraduate statistics courses. These challenges are occurring while the number and diversity of students enrolling in statistics is increasing. Cognitive learning theory is a hopeful avenue for educators faced with the challenges and growth in introductory statistics courses.

Cognitive Learning Theory

Cognitive learning theory examines the underlying, often unconscious, thought processes of the learner. This metacognition affects students' attitudes and motivation.

Implicit theories of intelligence are an example of a cognitive learning theory in which individuals hold beliefs about the nature of learning (Mangels et al., 2006). These mental constructs involve and affect an individual's self-efficacy, self-esteem, and implementation of self-regulation, all of which are important aspects of academic achievement (Good et al., 2012; Usher, 2009). To provide background knowledge about the metacognition of statistics learners, components of cognitive learning theories including students' attitudes toward content areas, implicit theories of knowledge, motivation, and the theories around self are addressed in following sections.

Attitudes. An important aspect of education is the attitude that individuals hold toward areas of study. In mathematics, there is evidence that attitudes affect achievement and participation (House, 2006; Tapia, 1996). Evans (2007) found similar correlations between attitudes and achievement in statistics classes. This creates a challenge for statistics educators as "the results of a number of studies point to the persistence of negative attitudes towards mathematics as students ascend the academic ladder" (Aiken, 1970, p. 556).

Students' attitudes toward statistics, like mathematics, are also an important consideration. Ruggeri (2011) observed that the largest change in students' attitudes and anxiety in an introductory statistics course was a decrease in students' reported enjoyment of statistics. Unfortunately, Evans (2007) found no methods in his research for instructors to help improve student attitudes. It is clear that attitudes impact students' achievement in statistics. More research is necessary to understand and address the issues of statistics anxiety and negative attitudes toward statistics (Ruggeri, Diaz, et al., 2008).

Implicit theories of knowledge. Implicit theories of knowledge are a researchable construct of cognitive learning theory. Implicit theories are metacognitive processes that an individual holds concerning beliefs about their cognitive abilities (Boekaerts et al., 2003; Burns & Isbell, 2007; Mangels et al., 2006). Anderson (1995) referred to implicit theories as knowledge structures that influence affective reactions and behaviors. Implicit theories of knowledge are an example of Bandura's (1999) social cognitive theory which states that people do more than react to life events and brain functions, but consciously develop meaning and beliefs in response. Each person has belief systems that provide meaning and organization for their experiences (Burns & Isbell, 2007; Dweck, 1999). An individual's belief system concerning his or her ability to learn affects motivation, goal setting, and persistence since individuals will not exert effort for tasks that they see as unachievable.

Bandura (1999) posited that one of the major functions of thought is to help individuals predict events and exert control over events that they find important. Mindset theory lends itself readily to applications that enable individuals to enhance their well-being and accomplishments through an examination of their cognitions (Bandura, 1999).

Implicit theories of knowledge are an important area of social cognitive learning theory that examines an individual's beliefs about knowledge. A substantial body of research has examined student learning from a variety of perspectives with a recent focus on metacognition and factors that influence student's metacognition (Ames, 1992; Boese et al., 2013; Burns & Isbell, 2007; Chiesi & Primi, 2010; Stevenson, Lee, & Stigler, 1986). This literature clearly indicates that students' views regarding the nature of acquiring knowledge have a large impact on behaviors and achievement. Cutts (2008) stated that individuals' theories of intelligence in a specific area are instrumental in their future achievement in that domain.

Individuals tend to hold two distinct belief patterns regarding knowledge (Anderson, 1995). Persons that believe intelligence is static hold an entity mindset. In this view, there is little one can do to improve intelligence. This is in contrast to incremental theorists, who believe that intelligence can be developed.

The development and implementation of the Intelligence Quotient (IQ) test is a good example of the two mindset views regarding implicit theories of knowledge. The IQ test has been used since the beginning of the twentieth century to determine academic ability (Bruning et al., 2011). Over the past century, many individuals have used the IQ test as proof of academic ability and potential.

Surprisingly, the French psychologist Alfred Binet, the test creator, would not agree with this application. As an incremental theorist, Binet believed that intelligence is malleable, not a fixed trait (Bruning et al., 2011). Binet developed the IQ test to measure intelligence at a specific point in time. His goal was to identify students in the Parisian schools that were not on track so that interventions could be implemented to rectify the cognitive lag (Dweck, 2006; Dweck & Leggett, 1988). In response to the training procedures he designed for students, Binet stated, "the intelligence of these children has been increased. We have increased what constitutes the intelligence of a pupil: the capacity to learn and to assimilate instruction" (Dweck & Leggett, 1988, p. 263). Binet clearly believed in the malleability of individual's intelligence. This theory that intelligence is malleable in all domains, including statistics knowledge, is foundational in this study.

Motivation. Another area of study within social cognitive theory that may influence the student of statistics is motivation. Cognitive learning theory posits that "motivation is a state, not a trait" (Syed, 2013, p. 1). This implies that it is possible to improve students' motivation through a deep understanding of how individuals learn and are motivated to act (Huetinck & Munshin, 2008). Motivation is closely tied to the idea of expectancy and subsequent persistence.

Students' motivation schemas are inter-related beliefs about themselves. One factor that affects students' motivation is their beliefs about their ability to succeed. Bandura's (1999) expectancy value theory describes motivation as a product of individuals' expectations of specific outcomes and the value that they place on those outcomes. This belief in desirable outcomes affects individuals' motivation to persist when faced with obstacles. Individuals that do not believe they are capable of a desired outcome have little motivation to act based on expectancy value theory (Usher, 2009).

Beliefs regarding successful outcomes also play a role in motivation to learn. Educators have known for some time that an important factor in students' academic motivation is their beliefs about their ability to succeed (Ames, 1992; Elliott & Dweck, 1988; Zimmerman, 2000). These beliefs are largely interpretations of the context in which students are offered opportunities to learn and grow through similar experiences from their past (Syed, 2013). Expectancy value theory has important implications for the mathematics classroom as students who hold entity beliefs may not have the ambition necessary to seek help in the face of obstacles if they do not believe they have the ability to acquire mathematics knowledge (Kim & Kellert, 2010).

It is not surprising that many students face motivational issues regarding mathematics if they hold a low expectancy for success and a low value of mathematics. It is against this backdrop that mathematics teachers hope to instill an internal motivation in their students to master mathematics (Huetinck & Munshin, 2008). Teachers respond by valuing effort, designing mastery-oriented classrooms (Ames, 1992), viewing failure as an opportunity to learn, and creating classroom environments that encourage students to persist (Syed, 2013).

Students who persist when faced with failure are not motivated by outcomes, but see failure as progress toward learning (Syed, 2013). Bandura (1999) described these students as tenacious strivers who "believe so strongly in themselves that they are willing to exert extraordinary effort and suffer countless hardships and disappointments in pursuit of their vision" (p. 32).

Perseverance is an important ability for students in the mathematics classroom. The Common Core State Standards Initiative (2012) lists persevering as one of the eight standards for mathematical practice. The National Science Foundation also recognizes perseverance as a critical factor in learning math and the lack of perseverance as a factor in the current shortfall of students in mathematics related fields (Rattan, Good, & Dweck, 2012).

Of additional concern for developing persistence in students is the popular practice of identifying strengths and weaknesses. "The idea that people's areas of weakness should be accepted as long as they focus on developing and maximizing their strengths, has become a prevalent one in American society" (Rattan et al., 2012, p. 731). This practice aims to build self-esteem, but ultimately pushes students away from domains such as math and science that they perceive as difficult. It ultimately contributes to the shortage of students in mathematics and science fields (Rattan et al.). Motivation is a complicated construct that is interrelated with students' beliefs about their abilities and their expectation for success. Students' beliefs about their abilities are then explored in more detail.

Self-efficacy, self-esteem, and self-regulation. Individuals' implicit theories of knowledge have also been connected to self-esteem, self-efficacy, and self-regulation. The entity and incremental mindsets are distinct knowledge structures with different self-concepts and sources of self-esteem (Anderson, 1995; Dweck & Leggett, 1988). Self-esteem is an evaluation that individuals hold concerning their personal worth. A study of undergraduate students at the University of California at Berkley found that college students with entity mindsets had, on average, lower levels of self-esteem when compared to students with incremental mindsets (Robins & Pals, 2002). Additionally, the gap in self-esteem between students with fixed and growth mindsets grew significantly throughout their four years in college.

Beliefs that individuals hold regarding their expected success are closely tied to self-efficacy. Self-efficacy refers to what students believe about their academic capability to achieve (Zimmerman, 2000). It is the result of emotional, cognitive, or motivational processes and develops when students feel that they have mastered sub-skills or achieved milestones (Usher, 2009). Self-efficacy is domain specific and plays an important role in many areas including mathematics (Zimmerman, 2000). To underscore the importance of self-efficacy, prior mathematics experience has been shown to be less predictive of problem solving success than a student's self-efficacy

(Zimmerman, 2000). Peters (2013) found a positive relationship between students with high mathematics self-efficacy and high levels of mathematics achievement in research with 326 college algebra students across the country.

Connections between self-esteem and individuals' implicit theories of knowledge have also been shown. Dweck (1999) performed a study of college students with Michael Chaefets-Gitin and Melissa Kamins in which they found that theory of intelligence, achievement goals, and self-worth had a highly significant relationship to each other. Entity theorists' self-esteem is raised and maintained by demonstrating their abilities (Cutts, 2008; Dweck & Leggett, 1988). Incremental theorists acquire self-esteem through pursuing and making progress on mastering difficult tasks that they deem valuable (Ames, 1992; Dweck & Leggett, 1988). Self-esteem is bolstered for incremental theorists when they use their abilities to their potential and is experienced when an individual strives for things that are of value to them (Dweck, 1999).

Individuals' perceived sense of control is also a factor in self-efficacy. Banks and Woolfson (2008) found that middle school students who perceived they were low achievers reported less of a sense of control over their failures than those who believed they were high achievers. This lack of control and low self-efficacy in a domain encourages students to respond in ego protecting manners. To maintain self-esteem, students need either to succeed in a specific domain or, if success is not possible, disengage and disidentify from the domain (Aronson et al., 2002). The possibility of disengaging with mathematics is what makes an entity mindset so dangerous. It is important that teachers recognize when students disengage from class as a result of their perception of a lack of control over their academic outcomes. One way to help students regain a sense of control is self-regulation (Usher, 2009).

Self-regulation refers to processes that individuals implement to turn ability into skills (Usher, 2009). There is evidence of a reciprocal relationship between self-efficacy and implementing self-regulation with self-efficacious students being more likely to make use of cognitive and metacognitive strategies (Ames, 1992; Usher, 2009). Interestingly, not only does self-efficacy improve self-regulation, but increased self-regulation also leads to an increase in student's self-efficacy. This creates a self-empowering cycle that enhances both confidence and competence.

Bandura's (1997) expectancy value theory also plays a role in self-regulation as students who do not believe they will be successful are unlikely to use self-regulation for their learning (Usher, 2009). This implies that not only students' domain efficacy, but also their efficacy in their ability to learn is important. Ames (1992) posited that the use of self-regulatory skills is also dependent on students' belief in their ability to manage their learning.

Self-regulation plays an important role in the mathematics classroom. Students with high self-efficacy adeptly use self-regulatory skills when learning mathematics (Usher, 2009). In contrast, low self-efficacious students struggle with their work and do not seek help from teachers as frequently (Kesici et al., 2011). Students' beliefs about their mathematical ability also affect their internal dialogue. What is clear is that students with high self-efficacy set higher learning goals, monitor their success toward those goals, and navigate obstacles with increased motivation while those with low self-efficacy set lower goals and experience higher levels of stress and disheartenment at obstacles (Usher, 2009). Self-efficacy, self-esteem, and self-regulation are interrelated aspects that have a critical influence in students' behavior and achievement in the classroom.

Helpless responses. An area of interest for researchers in cognitive learning theory is how students respond to challenges. Many students when confronted with obstacles respond with helpless behaviors. Helplessness is a common response among students with low self-efficacy. The helpless response is a pattern in which the student avoids challenge, shows decreased performance when facing obstacles, and demonstrates a tendency to measure themselves by their failures (Diener & Dweck, 1978; Dweck & Leggett, 1988; Grant & Dweck, 2003; Kamins & Dweck, 1999). The helpless response has been shown in children as young as three-and-a-half years old and cannot be predicted by a student's present ability (Dweck, 1999). Both accomplished and novice students are equally likely to respond to setbacks with attributions and abandoning the task; however, there is evidence that the helpless response is more common among students with an entity mindset. Students who measure their success based on their performance are more likely to display helpless responses to failure, especially if the failure is attributed to an uncontrollable source (Banks & Woolfson, 2008; Dweck, 1999).

Dweck and Leggett (1988) studied children of all ages in numerous settings to determine what caused some children to persist and enjoy challenge, while others buckled under the stress and exhibited helpless behaviors. They concluded that helpless children viewed failures as an indictment of their academic ability that was impossible to overcome (Dweck & Leggett, 1988). Helpless students' implicit theory of knowledge dictated that effort was useless, bringing about defensive maneuvers. Dweck (1999) noticed in a study of students labeled as helpless that one third denigrated their intelligence at the introduction of challenge, while none of the growth-oriented students did. Additionally, Dweck and Leggett (1988) found in a study of problem solving that two-thirds of children identified as helpless participated in irrelevant verbalizations and showed a marked decline over repeated trials. Some of the decrease in performance could be attributed to poor strategy selection. Helpless children when faced with a setback were less likely to devise new strategies and more likely to abandon effective strategies and repeat ineffective strategies (Dweck & Leggett, 1988).

In another study of elementary school children, Dweck (1999) used problem solving to examine the helpless response. Students were given multiple problems that they could successfully solve. These easier problems were followed by problems that were beyond their ability. Two-thirds of students who held a growth mindset, as measured by a version of the Theories of Intelligence (TOI) scale developed by Dweck, issued an optimistic report about their ability to solve difficult problems. Two-thirds of students labeled as helpless expressed negative emotions when confronted with the difficult problems despite the fact that they had been happily involved with easier problems only minutes earlier. Remarkably, the helpless response not only affected students' performance on the difficult problems, but subsequent problems as well. When students were presented with easier problems similar to what they had previously solved successfully, students labeled as helpless were less likely to solve the easier problems than the mastery-oriented students were. Helpless students had lost confidence in their intelligence and were unable to access the skills and knowledge that they had previously demonstrated.

The helpless response is of particular concern in mathematics education since high school and college students are asked repeatedly to engage in new types of thinking that may be difficult to relate to previous knowledge. A resulting disequilibrium can occur when students take their first algebra, geometry, or statistics course. This disequilibrium is concerning for students prone to the helpless response as they may respond helplessly and prematurely decide that they lack the ability to succeed in mathematics (Dweck, 1999). The helpless response with its challenge avoidance and deteriorated performance is a dangerous pattern for many students and contrasts resilient students.

Resilient responses. A resilient child holds a different view of obstacles and consequently responds with different behaviors. A resilient child can withstand adversity and recover from setbacks and failures (Donohoe et al., 2012). Hoerr (2013) referred to the character of resilient students as grit and used the term good failure to refer to failures that ultimately make the student stronger. Duckworth added that grit also includes a commitment and loyalty to mastery that remains over many years (Perkins-Gough & Duckworth, 2013). Helpless children stand in contrast lacking the grit and commitment to strive through setbacks.

Resilient students hold a different view of failure. Winston Churchill, prime minister of the United Kingdom during World War II, epitomized grit and resiliency in his leadership. He is quoted as saying, “Success is the ability to go from failure to failure without losing your enthusiasm” (Hoerr, 2013, p. 84). All students face setbacks in their mastery of learning at some point throughout their education. Resiliency is an important trait for students to develop to help confront obstacles.

Resiliency also allows students to exert effort to achieve mastery. Malcolm Gladwell (2008) in his book *Outliers* examined numerous popular icons who persevered and demonstrate grit including The Beatles and Bill Gates. As a result of his research, Gladwell popularized the 10,000-hour rule. The 10,000-hour rule claims that without a significant amount of practice and effort, individuals cannot master difficult skills. The Beatles and Bill Gates, as well as athletes, musicians, and professionals, all display resilience and tenacity as they devote large amounts of time to mastering their craft.

Students' implicit theory of knowledge plays an important part regarding their resilience. Blackwell et al. (2007) stated that positive associations exist between an incremental mindset and positive effort beliefs, learning goals, decreased helpless attributions, and increased effort-based strategies. Dweck and Duckworth also collaborated on the role of persistence and mindsets and found that students with incremental mindsets tended to be grittier in their approach to work (Perkins-Gough & Duckworth, 2013). This has important repercussions for mathematics. "If a student believes that mathematics knowledge is gradually acquired and the acquisition process is effortful, he or she might not give up so easily and might be persistent in studying " (Kim & Kellert, 2010, p. 408).

To summarize, cognitive learning theory is an overarching view regarding the internal thoughts that students hold about learning. It covers many areas including attitudes, mindsets, and motivation. It also helps explain students' self-efficacy, self-esteem, and implementation of self-regulation skills. Students' theory of intelligence, self-efficacy, and self-esteem are aspects that determine students' responses to failure such as helplessness or resilience.

Attribution Theory

Attributions are an important aspect of cognitive learning theory that can have both positive and negative influences on students. Bernard Weiner (1985) proposed attribution theory in the mid-eighties. Since then it has been promoted by educators and educational psychologists as an effective method to improve achievement and motivation for students with academic difficulties (Banks & Woolfson, 2008; Robertson, 2000). Attributions are classified along three dimensions: locus, stability, and controllability (Banks & Woolfson, 2008; Boekaerts et al., 2003). Locus refers to the location of the cause as internal or external to the student (Shores & Smith, 2010). Stability is a belief about the possibility of change for the cause and controllability refers to the ability to affect future outcomes (Syed, 2013).

When students fall behind academically, it is important for teachers to understand what is causing their struggle (Shores & Smith, 2010). Of particular concern are failure attributions that are stable and beyond a student's control (Hall, Hladkyj, Perry, & Ruthig, 2004; Shores & Smith, 2010). If students perceive that they cannot change a situation (stable attribution), their self-efficacy suffers and expectations for future success are greatly harmed (Banks & Woolfson, 2008; Shores & Smith, 2010). There is a strong psychological benefit for students to use stable failure attributions because it protects their sense of ability (Banks & Woolfson, 2008; Boese et al., 2013). If students have no control over their failure, they cannot place blame on themselves. There is evidence that the type of attribution affects students' academic achievements. House (2006) found in an examination of adolescent students in Japan that algebra students who attributed their success to external factors earned lower test scores. In contrast, higher scores were earned by students who reported enjoying mathematics.

Attributions occur frequently in mathematics. Boekaerts et al. (2003) found evidence in their work with 113 middle school students in the Netherlands that attribution patterns are different in mathematics than the subjects of native language and history. Rarely do students attribute success in mathematics to ability, but more frequently to easier tasks and effort expended. Interestingly, task difficulty still plays a small role for failure attributions in mathematics, with ability being the largest attribution. Thus, students attribute success in mathematics to effort, but failure to ability (Boekaerts et al., 2003). Effort is an important causal attribution since it is closely tied to a growth mindset. Students will use effort attributions only if they believe that their intelligence can be improved. This concurs with research from Harari and Covington (1981) who found that students who used effort attributions persisted longer in tasks following a failure.

Connections between attributions and self-efficacy have also been observed. Students who believed they were lower achievers, regardless of their teacher's perception of ability, displayed more maladaptive attributions (Banks & Woolfson, 2008). This finding points to the importance of attributions not only to low-achievers, but also for students who perceive themselves as low-achievers. Additional research examined an individuals' ability to estimate one's skill. Dweck (2006) found that people were especially weak at identifying their ability; however, a majority of the variance was due to the inaccuracy of individuals with fixed mindsets. Attributions form a foundation upon which mindset theory is built and continue to play an important role in students' behaviors.

Mindset Theory

It is important to look beyond attributions to a consideration of mindset theory in more detail. Multiple aspects will be examined in this section including a thorough examination of both entity and incremental mindsets and the role that mindsets play among individuals with high intelligence. Next, the implications that mindset has for persistence, effort, and in mathematics in particular will be discussed. The section will close with an examination of the connections between mindsets and goal orientations.

Dweck's research on mindsets grew from the foundation built by Weiner's (1985) work on attribution theory. Dweck (1999) was fascinated with the helpless response, attributions, and their consequences. These behaviors formed the foundation of mindset theory and continue to play an important role. Dweck (1999) began her research from an interest in how individuals handle setbacks. She noticed that "many of the most accomplished students shied away from challenge and fell apart in the face of setbacks" (p. 5) while other students with less skill eagerly embraced challenge and were reinvigorated by setbacks. Dweck concluded that vulnerability was not based on the realities of students' abilities.

According to Dweck (1999), mindset theory is more comprehensive than attribution theory as it outlines the personal theories and goals that form the two mindsets. One weakness of attribution theory is that it lacks an explanation for why individuals would seek challenge since goals are not a part of the theory. The theory of mindsets is more inclusive and dynamic than attribution theory since more than causes of outcomes are explored, but also mediators of behavior (Dweck, 1999). Finally, the focus of attribution theory is on the locus, stability, and controllability of causes whereas mindset emphasizes how the individual perceives the cause. These perceptions influence an individual's future response.

Another impetus for the introduction of mindset theory is new research in cognitive neuroscience. Research in recent decades has revealed how the brain functions and that its ability to grow and increase intelligence is much greater than was previously assumed (Cutts, 2008; Dweck, 2010; Good et al., 2003). Knowledge about the increased neuroplasticity of the brain has powerful effects for individuals. Students with low self-efficacy are empowered by the malleability of intelligence that they too can achieve academic success (Donohoe et al., 2012). Educators promoting a growth mindset compare the mind to a muscle that strengthens with development and use (Good et al., 2003). Building off these cognitive neuroscience findings, some curricula have begun to emphasize the importance of students' mindsets. For example, several textbooks in the Scholastics series start with a two week unit on mindsets and neuroplasticity (Sparks, 2013).

Implicit theories of knowledge are dynamic and there is evidence that individuals' tendencies change as they grow and develop. Dweck (2006) stated that everyone is born with an intense desire to learn and it is not until children can evaluate themselves that they become afraid of challenges. Infants constantly make mistakes with very little concern about them. Babies' mishaps are not alarming to adult observers because of an understanding that mistakes are a natural aspect of learning. Students' mindsets begin to change as they mature. Research with seven and eight year old students has shown that patterns associated with the entity mindset are already seen in children at this early elementary age (Heyman & Dweck, 1998).

There is evidence that the valuation of effort and ability change with development as well. Harari and Covington (1981) found that early elementary students emphasized the role of effort in intelligence. This valuation gradually shifted throughout the educational experience to an emphasis on the role of ability in college students. A detailed examination of each implicit theory of knowledge follows.

Entity. Individuals with an entity, or fixed, mindset believe that ability is static and unchangeable. They believe that an examination of their current abilities predicts their future capacity (Dweck, 1999). The cardinal rule for students with entity mindsets is "*Look smart at all costs*" (Dweck, 2010, p. 7). Students with a fixed mindset feel smart with easy, low-effort successes, and by outperforming other students (Dweck, 1999). The self-imposed rule to look smart prohibits entity theorists from seeking remediation when necessary. It also affects performance at school since students may perceive school as a place of testing and judgment about their abilities (Dweck, 2008). One response that many students have when faced with challenge at school is self-handicapping. A student who self-handicaps withholds effort and consequently may underperform. This allows the students to still think highly of themselves by preserving the belief that they could have succeeded if they had applied themselves (Dweck, 1999).

Students' theory of intelligence also affects their behaviors with students holding entity mindsets responding differently to failure (Burns & Isbell, 2007). In a study of pre-medicine students at Columbia University, Dweck (2010) found that "students in a fixed mindset believe that if they had the intelligence, it would carry them straight through to perfect performance" (p. 7). Against the backdrop of expected perfection, students with fixed mindsets perceived one poor grade as a measure of their ability and subsequent performances never recovered. This demonstrates the crippling effects of entity beliefs and how they lead individuals to make rigid judgments, restrict their capabilities, and limit the paths they can pursue (Dweck, 1999). Entity mindsets are in contrast to the incremental mindsets held by other students.

Incremental. Individuals who hold an incremental, or growth, mindset think and behave in different manners than entity theorists. Dweck (1999) and Claudia Mueller found in interviews with college students that entity theorists tended to define intelligence as inherent and a predictor of potential, whereas college students who were incremental theorists defined intelligence as a person's present skills and knowledge. The cardinal rule for students with incremental mindsets, *learn*. "Students in a growth mindset do not want to waste their time looking smart on tasks that offer them nothing else. They overwhelmingly want tasks that stretch their abilities and teach them new things" (Dweck, 2010, p. 8). Incremental theorists thrive when they are growing and learning. They feel smart when they are fully engaged, stretching themselves, and putting their skills to use (Dweck, 1999).

High intelligence. A common misperception is that the only students at risk of an entity mindset are low achieving students. No difference in academic ability has been found between students who hold entity or incremental theories, yet high achieving students who hold entity mindsets often go unnoticed (Sparks, 2013). Dweck (2006) reminded anyone interested in mindset theory, that "it's not always the people who start out the smartest who end up the smartest" (p. 5).

Aronson et al. (2002) conducted a study with 109 Stanford University undergraduate students in which one group was taught about an incremental theory of intelligence and the control group was taught about Gardner's theory of multiple intelligences. At the end of the semester, the students taught about an incremental mindset had higher grade point averages when controlling for SAT scores. This contradicts the assumption that highly skilled students would persevere through challenges. Rather, many highly skilled students are more concerned with failure than mastering their learning (Dweck, 1999). As a result, they doubt their ability and fade when faced with obstacles.

There is no evidence that students' initial intelligence level or self-efficacy predicts a tendency toward either mindset. Dweck (1999) found evidence that students with low confidence in their intelligence and who hold incremental mindsets still display challenge-seeking behaviors and persist in mastering difficult tasks. Students' mindsets, regardless of their intelligence, are important predictors in their behaviors and tenacity.

Persistence. Persistence is a vital characteristic in students that predicts achievement and behavior. In this section, evidence of differences in persistence based on students' implicit theory of knowledge, and their self-confidence will be examined as well as connections between persistence and depression.

Persistence in the face of setbacks is an important factor in understanding how individuals initially assessed with similar skill levels can achieve at drastically different levels. David Dockterman (2013), adjunct professor at Harvard University and curriculum designer for Scholastic, has an interesting perspective regarding perseverance and mathematics. He noted that students are willing to experience failure as much as

80% of the time when playing a video game, yet many are unwilling to approach mathematics with a similar mindset. In a fixed mindset, a setback signifies a deficiency in ability; a deficiency that is seen as permanent (Dweck, 2010). When students approach mathematics with a fixed mindset, their response to failure may ultimately affect their overall mathematics achievement (Zimmerman, 2000).

There is evidence that individuals' implicit theories of knowledge also affect their physiological response to criticism. Mangels et al. (2006) researched differences in brain wave activity of undergraduate students at Columbia University holding both entity and incremental mindsets as measured by the TOI scale. In the study, college students were given a test of their geographic knowledge and subsequently provided with correct answers to their errors. Brain wave analyses demonstrated differences between students with incremental and entity mindsets based on their mindset. Entity theorists engaged in a shallower level of semantic processing after feedback for incorrect answers than individuals with incremental mindsets. Mangels et al. (2006) concluded that students with entity theories viewed feedback as threatening to their self-efficacy instead of as an opportunity to develop their abilities. Additionally, when students were unexpectedly retested on the questions that they initially erred on, "incremental theorists corrected significantly more errors than did entity theorists overall" (Mangels et al., 2006, p. 79). It appeared that the alarm students with entity mindsets experienced compromised their ability to learn from their mistakes. Dweck (1999) noted the irony that students who could gain the most from correction and remediation are those who most clearly avoid it. Clearly responding to failure is an important skill for students.

There are effective methods to mediate the effects of setbacks. Brain research indicates that a positive approach to challenging situations and difficulty can mitigate the emotional effects of negative feedback (Mangels et al., 2006, p. 83). It is not the confidence that an individual brings into a challenge, but the ability to respond in a confident, non-defensive manner that helps students respond positively to negative feedback (Dweck, 1999). This ability allows students with incremental mindsets, regardless of self-confidence in their ability, to persevere and continue to seek challenge in pursuit of mastery (Dweck, 1999). Their incremental framework allows them to see feedback not as an evaluation of themselves, but as a learning experience. This allows them to welcome feedback as an opportunity to grow (Dweck, 1999; Mangels et al., 2006).

Interestingly, individuals' confidence in their intelligence does not protect those with entity theory mindsets from helpless responses in the face of challenge. Many confident individuals do not want their intelligence stringently examined and their confidence evaporates when confronted with obstacles (Dweck, 1999). In working with elementary school students on mathematics problem solving, Dweck (1999) researched if successful experiences would help students' confidence and perseverance. "Training that gave students just success experiences did not help them to cope with failure, even though they showed confidence and enthusiasm while the success lasted" (p. 57). Another weakness of an entity mindset is that students feel no need to approach challenge. Students receive a boost from success, but the vulnerabilities of an entity mindset remain and they often avoid challenge (Dweck, 1999). Their desire to look smart will result in avoidance of challenge.

An example of the desire to look smart occurred in a study of 29 undergraduates which examined students' response to feedback on a 30-minute speed-reading activity (Nussbaum & Dweck, 2008). Prior to the speed-reading activity, individuals were fostered to hold either an entity or incremental mindset. After speed-reading, students were given feedback on their performance and given the opportunity to examine other students' strategy use. Interestingly, students in the incremental mindset condition chose to examine strategies of those who performed better than they did in an effort to learn from their mistakes. In contrast, students in the entity condition chose to compare their reading strategies to peers who performed worse than they did, apparently in an effort to bolster their self-esteem. The difference in the comparisons between the entity and incremental groups statistically significant.

An individual's mindset has also been shown to affect response to depression. Unpublished qualitative research performed by Baer, Grant, and Dweck found that depressed undergraduate students with fixed mindsets let their studies slide while depressed students with growth mindsets studied even harder and coped with determination (Dweck, 2006). Zhao, Dweck, and Mueller (1998) found in a separate study of how undergraduates respond to setbacks, even a hypothetical failure brought on 'depression-like' moods and thoughts. This depression response could start a negative cycle since depression has also been connected with maladaptive attributions (Banks & Woolfson, 2008). The understanding that students can build their intelligence allows them to take risks and learn from mistakes instead of dwelling on their lack of perfection (Sparks, 2013). Persistence is a valuable characteristic in students that also affects the amount of effort an individual is willing to expend in mastering a skill.

Effort. Effort is an important factor in education that changes while students mature. An individual's view toward exerting effort is another distinction between an entity and an incremental mindset (Dweck & Leggett, 1988). Dweck (2010) noticed in her work with students of all ages that "the most motivated and resilient students are the ones who believe that their abilities can be developed through their effort and learning" (p. 6). In an incremental theory, students understand that effort plays an important role in achievement (Dweck, 1999). Confidence for these students stems from the belief that effort will assist them in their pursuit of mastery. For individuals with an entity mindset, effort is threatening because people who are naturally able should not need to exert effort (Dweck, 2006).

The emphasis that entity and incremental theorists place on effort in achievement also varies. Mueller and Dweck (1997) researched college students for their perceptions of the role of effort and ability in intelligence. Among students who held an entity mindset, 35% of academic achievement was attributed to effort and 65% to ability. To the extent that entity theorists attributed success to ability, incremental theorists valued effort attributing 65% of achievement to effort and only 35% to ability. This emphasis on success due to ability causes entity theorists to devalue effort. Dweck (1999) posited that "it would be hard to maintain confidence in your ability if every time a task requires effort, your intelligence is called into question" (p. 41). This belief puts students who easily excel particularly at risk to undervalue effort and not exert it when needed (Sparks, 2013).

A devaluing of effort also affects students' behaviors regarding studying and persistence. Harari and Covington (1981) noticed in a problem-solving activity that children who emphasized effort for the cause of their previous success persisted longer on a posttest and consequently solved more problems. In another study, they found that older students prefer to be viewed as having ability rather than as hard workers. A majority of fourth-grade students believed that intelligence was malleable, but by sixth grade, effort was no longer valued. After their work with first graders through college freshman, Harari and Covington (1981) concluded that,

> the progressive grade-wise devaluation of effort is associated with emerging beliefs among older students that (1) studying does not necessarily lead to success, since ability is the more crucial factor; (2) that high effort, irrespective of outcome leads to lower ability estimates, and conversely, (3) that low effort in success enhances a reputation for competency while obscuring the causes of poor performance in failure. (p. 26)

Study habits are also shaped by individuals' valuation of effort. An interesting study by Kim and Kellert (2010) examined the study habits of undergraduates in introductory mathematics classes. Students were randomly divided into various groups and, throughout the semester, they received emails with messages according to the group they were assigned. A matrix of message types was used. One-third of the group received motivation and volition messages that gave relevance to mathematics and encouraged goal setting. Another third received belief-change strategy e-mails that examined the speed of learning and ability to learn. The final third received a combination of both motivation and volition and belief change strategies messages. Each of the three groups was also divided in half to receive either group or personalized emails. Additionally, a control group was used which received no messages, but did report their time studying.

Negative trends in study habits were seen in all groups of students with the exception of students who received belief change strategies with personal messages. Interestingly, the belief change strategies messages provided participants with no techniques to improve study habits. Additionally, students who received the personal belief messages showed an improvement in their attitudes as measured by the Fennema-Sherman Mathematics Attitudes questionnaire, although it was not a statistically significant change (Fennema & Sherman, 1976). This study provides evidence that a student's mindset is alterable and that the underlying message of the malleability of intelligence encourages students to respond with behaviors that promote learning (Dweck, 1999).

As demonstrated in the studies above, effort is required for students to achieve; however, many students see effort as indicative of lower ability (Dweck, 1999). This view affects students' valuation of effort, study habits, and ultimately their achievement in negative ways. In application, belief-change messaging in college mathematics classes was shown to positively impact mathematics attitudes.

Mindsets toward mathematics. Implicit theories of knowledge are an important consideration in mathematics education as well. Historically, the mathematics community has emphasized innate ability. The National Research Council (1991) published a book on falsehoods in undergraduate mathematics, which includes the myth that "success in mathematics depends more on innate ability than on hard work" (p. 10). This concurs with the claim that mindsets can be quite domain-specific for many individuals (Anderson, 1995). Dweck (2008) argued that students tend toward an entity view of knowledge in mathematics. Good et al. (2012) agreed stating that "perhaps nowhere is the belief in the fixed nature of math ability more entrenched than within the mathematics community itself, which relies on a 'talent-driven approach to math'" (p. 70).

Evidence is mounting regarding the role that students' mindsets play in learning mathematics (Dweck, 2008). Blackwell et al. (2007) conducted a landmark study on the impact of a growth mindset in their longitudinal study of 373 New York City middle school students' mathematics performance during the transition to junior high. Significant evidence was found that students with incremental mindsets improved their achievement in mathematics over the two years in junior high compared to students with fixed mindsets who showed no change. The growth pattern for math achievement differed based on the student's mindset as measured by the TOI scale. Dweck (2008) concluded that it was the students' implicit theories of intelligence that helped them persist across this difficult school transition.

One interesting result of Blackwell et al.'s (2007) study was that many of the students who demonstrated the most impressive improvements in class standing were incremental theorists who held a low confidence in their academic abilities. Ultimately, it was students' theory of intelligence that helped them successfully navigate the transition to junior high more than their confidence in their intelligence.

Theory of intelligence offers a promising resource to improve mathematics education (Sparks, 2013). "Motivating learners to engage in learning tasks is of obvious interest to teachers and a constant challenge, particularly for mathematics instructors"

(Kim & Kellert, 2010, p. 407). One practice that has hindered motivation and a growth mindset in mathematics is the perception that mathematical geniuses effortlessly master difficult concepts and theories. Dweck (2008) suggested that depicting mathematics and science role models as people who were dedicated to their research invites any student to become a member of the mathematics and science community. An incremental mindset helps students see that intelligence, including genius, is developed through sustained effort. Given students' natural inclination toward entity mindsets in mathematics class, it is important to examine methods to foster incremental mindsets in students.

Performance and mastery goals. One of the largest areas of difference between the entity and incremental mindsets is in students' goal setting. Student goals can be divided into two main categories: performance and mastery (Ames, 1992). Performance goals focus on demonstrating an individual's competence. An example of a performance goal is the desire to look like a proficient skater when ice skating with friends. An individual with this orientation may set a performance goal of not falling during an outing to the ice rink. Learning goals focus on mastering a skill. An example of a learning goal is the desire to become a proficient ice skater. An individual with this learning goal will not see falling as a failure, but as a learning experience.

Research has shown that theory of intelligence is a reliable predictor of children's goal orientation (Dweck & Leggett, 1988; Heyman & Dweck, 1998) and that goal orientations are associated with self-regulation, depression, anxiety, self-esteem, and response to failure (Dweck, 1999). Individuals that hold entity mindsets tend toward performance goals, while individuals with incremental mindsets favor mastery goals.

Performance goals emphasize measuring and validating ability by outcomes (Ames, 1992; Elliott & Dweck, 1988; Grant & Dweck, 2003). Although performance goals are necessary in certain situations, such as passing a driver's license test, a drawback of overemphasizing them is that students are vulnerable to the helpless response and not as able to overcome setbacks (Elliott & Dweck, 1988; Grant & Dweck, 2003). Another shortcoming occurs when students do not believe that they are capable of performing their goals. This belief results in decreased intrinsic motivation and deteriorated performance (Ames, 1992; Grant & Dweck, 2003).

Goal orientation also affects individuals' views of effort. Dweck and Leggett (1988) found evidence that students with performance goals viewed effort and ability as inversely related. It is this irony that can be paralyzing to students with performance goals. When they most need to exert extra effort, they draw back in a defensive response fearing that exerting effort reveals their ability as deficient. "Within a performance goal the ideal task maximizes positive judgments and pride in ability, while minimizing negative judgments, anxiety, and shame" (Dweck & Leggett, 1988, p. 261). In contrast, children with mastery goals would find these types of tasks boring and unfulfilling.

Mastery or learning goals are focused on skill acquisition and gaining knowledge. The ideal task for students with learning goals is one that maximizes growth of ability and the pleasure of mastery (Dweck & Leggett, 1988; Mangels et al., 2006). An advantage of learning goals is that children are not hampered by setbacks. Children with mastery goals see their current assessment of ability as irrelevant which allows them to take advantage of remedial activities when necessary and to seek out challenging tasks without a fear of failure (Dweck & Leggett, 1988; Mangels et al., 2006).

Mastery goals provide an inoculation to failure in many students. When students operate in a learning goal, they have no need to withdraw from difficulties because failure is not alarming to them but rather, an opportunity to learn (Dweck & Leggett, 1988). In fact, learning goals are associated with students seeking out challenging tasks, increasing motivation, and striving under failure (Grant & Dweck, 2003). Diener and Dweck (1978) performed two studies with fifth-grade students in which they monitored students' hypothesis-testing strategies during a discrimination learning task. They noticed that mastery-oriented children not only believed that they could overcome the obstacle, but they cherished the opportunity to do so. An interesting finding from Diener and Dweck's (1978) study was that mastery-oriented students did not show a decline in strategy use throughout the tests. In fact, students with mastery-oriented goals showed a tendency to use strategies that are more sophisticated in response to negative feedback.

An association between learning goals and self-regulated learning strategies has also been shown. Grant and Dweck (2003) found that learning goals were connected to active coping, consistent motivation, and increased achievement when faced with the possibility of failure. Students with learning goals also use deeper, more effective learning strategies to promote mastery (Dweck, 1999).

Another advantage of learning goals is that students are motivated to be deeply engaged in their learning (Huetinck & Munshin, 2008). In 1985, Dweck (1999) and Edwin Farrel conducted a study of junior high students in a science unit. They noticed that after a week of instruction on how to solve new problems, students who held learning goals produced 50% more material when attempting to solve a novel science problem.

The students' performance goals allowed them to persevere in problem solving and exert more effort.

As mentioned previously, performance goals are a necessary and natural part of daily life (Anderson, 1995). Individuals do need to demonstrate their mastery to receive privileges and advancements in many day-to-day situations. "The problem with performance goals arises when proving ability becomes so important to students that it drives out learning goals" (Dweck, 1999, p. 152). Students need both learning and performance goals to succeed in school, which makes it an asset for students to know when to adopt each type of goal orientation and to pursue each flexibly depending on the demands of the situation (Anderson, 1995; Dweck, 1999).

Grant and Dweck (2003) conducted five studies on undergraduate college students to learn more about the role of performance and mastery goals in achievement. They concluded that learning goals predicted active coping, positive reinterpretation of setbacks, and decreased behavioral and mental disengagement. Performance goals predicted a vulnerability to helplessness, self-denigration, and a withdrawal in response to setbacks and negative feedback. One study of particular interest asked students to imagine an academic failing scenario. Students with ability goals reported a statistically significant loss of self-worth in response to this imaginary failure agreeing to statements that they would feel like failures or think less of themselves (Grant & Dweck, 2003).

This section has outlined the difference between performance and learning goals and their connections to individuals' mindsets. The impact that goals have on effort, ideal tasks, response to failure, and student engagement was also examined. The section closed with an examination of research by Grant and Dweck (2003) concerning goal orientations.

Training

The literature review has demonstrated that maladaptive attributions and an entity mindset can be detrimental to a students' academic achievements. Fortunately, cognitive learning theory does not view students' attributions and mindsets as fixed. Training is a promising avenue to address these concerns (Anderson, 1995; Aronson et al., 2002; Banks & Woolfson, 2008; Donohoe et al., 2012).

Attribution retraining. Attribution retraining helps individuals alter maladaptive attributions. "One goal of attribution training is to have students focus on the tasks rather than be distracted by fears of failure" (Robertson, 2000, p. 112). Attribution retraining helps students find other ways to problem solve besides giving up. It also guides them to attribute their failures to inadequate effort, rather than lack of ability. Attribution retraining has largely taken the form of videos which emphasize positive versus negative thoughts and self-talk, persistence, flexible strategy use, and the role of external versus internal attributions (Boese et al., 2013; Hall et al., 2004). A key aspect of all attribution retraining is that it is followed by a consolidation exercise that helps students personalize the new information they received (Hall et al., 2004). Often consolidation consists of a discussion or writing task. Attribution retraining has also been combined with strategy instruction to help students simultaneously master successful attributions and academic behaviors (Robertson, 2000).

Numerous studies have demonstrated the effectiveness of attribution retraining (Berkeley, Mastropieri, & Scruggs, 2011; Boese et al., 2013; Calisto, 2013; Shores &

Smith, 2010). Boese et al. (2013) found that among failure-avoidant students, attribution retraining significantly increased the expectation of higher grades compared to a control group. Attribution retraining for at-risk college students has been shown to increase students' perceptions of control, success, emotions, and academic achievement (Hall et al., 2004). Robertson's (2000) examination of more than 20 studies in a meta-analysis of attribution retraining ranging from three days to 12 weeks found interesting evidence that attribution training that occurred over longer periods of time did not increase success compared to shorter treatments.

Incremental mindset training. Although attribution retraining has a longer history, training in an incremental mindset has also shown good potential in many studies (Anderson, 1995; Donohoe et al., 2012; Kim & Kellert, 2010). The goal of incremental mindset training is to help students understand the malleability of intelligence (Dweck, 1999). One way this is accomplished is by learning about the function of neurons and dendrites and the plasticity of the brain (Good et al., 2003). Many incremental mindset training programs for students also provide strategies for learning and self-regulation to support students' efforts (Sparks, 2013).

Studies have shown positive results for incremental mindset training. It has been linked to increased resiliency and academic performance in students (Donohoe et al., 2012). Cutts (2008) implemented four, 10 to 15 minute incremental mindset training sessions in first-year computer science courses at Glasgow University. The topic of each session follows (1) fixed and growth mindsets, (2) performance and learning goals, (3) response to feedback, and (4) role models and the neuroscience underpinning mindsets. Cutts found that students in the mindset training condition shifted toward a growth mindset over the course of the semester while students in the control condition shifted toward a fixed mindset as measured by the TOI scale. Cutts (2008) also concluded that the incremental mindset intervention was most effective when it was integrated with the learning.

Since the introduction of mindset theory, numerous groups have developed training interventions for classrooms. The premiere mindset training program is Brainology created by Dweck and Blackwell through the company Mindset Works Inc. (2008). Brainology was designed for fifth- through ninth-grade students and fosters a growth mindset in students through cartoons and activities. Donohoe et al. (2012) studied the effects of the Brainology curriculum on thirty-three 13 to 14 year-old students and concluded that the program led to a statistically significant increase in students' mindset scores as measured by the children's TOI scale both before and after the intervention.

It is clear that both attributions and theory of intelligences are alterable. One of the aspects of many of the interventions involved altering the environment. This is an important consideration for educators as they create classroom environments that spur their students to achieve.

Environment

The environment plays a crucial aspect in students' mindset development. Anderson (1995) hypothesized that cultures emphasizing the individual would foster entity mindsets. Dweck (1999) found that classrooms that emphasize evaluation and ability foster performance goals. Fortunately, classrooms that enhance achievement and mastery goals can also be created (Grant & Dweck, 2003).

The classroom environment has been shown to affect students' goal orientations. Elliott and Dweck (1988) assigned 101 fifth-grade students to learning conditions in which either a performance or learning goal was experimentally fostered through the task instructions of the importance of either evaluation or learning. The children were then asked to complete a pattern recognition task. The students had a choice between a task that would demonstrate their intelligence (performance option) or a task that they could learn from (mastery option). A statistically significant difference was observed between students' task selection. Students selected the mastery option when the importance of learning was emphasized and the performance option when the evaluative, performance environment was fostered.

Another interesting aspect of Elliott and Dweck's (1988) research involved the reactions and verbalizations that students made while completing the tasks. Students in the performance goal condition demonstrated helpless responses to setbacks and verbalized attributions for their failures. Students in the mastery condition displayed mastery-oriented responses and implemented achievement strategies. This demonstrates that it is possible to alter students' goal orientations through the environment.

Rattan et al. (2012) conducted a study in which they fostered entity and incremental mindsets toward mathematics in undergraduate students by asking students to read fictitious articles that they believed to be true, presenting evidence that mathematics ability is fixed or malleable depending on the mindset condition they were assigned. Next, they read a scenario in which a seventh-grade student received a 65% on a math test. Undergraduates in the entity theory condition were significantly more likely to endorse an entity belief toward intelligence and agree that the student was not smart enough for the math compared to students in the incremental condition (Rattan et al., 2012). This demonstrates the effect that reading a single article can have on an individuals' views of mathematical intelligence.

It has been shown that the classroom environment is an important consideration in mindset. It is important for educators and other adults to communicate admiration of hard work, challenge-seeking, and the value of mistakes (Dweck, 2008). Unfortunately, educators may unconsciously communicate performance goals and an entity mindset subtly through their actions and words.

Educators. Teachers, and their personal mindsets, play an important role in designing a classroom environment conducive to learning goals. There is growing evidence that teachers' mindsets affect their pedagogy and interactions with students (Good et al., 2012; Rattan et al., 2012). Teachers who hold entity mindsets create classroom atmospheres that are more judgmental, which can lead to decreased expectations of success for students (Dweck, 2006; Kamins & Dweck, 1999). Although no research has as yet confirmed this, Anderson (1995) hypothesized that individualistic cultures will foster more students with entity mindsets compared to collectivist cultures. Another factor that has a strong influence on mathematics learning for students is the teachers' beliefs related to mathematics (Bingolbali, Akkoç, Ozmantar, & Demir, 2011).

One implication of a fixed mindset for teachers occurs when they do not believe that students can improve their academic ability. This belief makes the teacher less likely to design experiences that assist students in developing their ability (Dweck, 2006). An educator's mindset, whether entity or incremental, creates a self-fulfilling prophecy for his or her students (Dweck, 2008). To emphasize the role that educators' mindsets play in students achievement, Cutts (2008) stated after implementation of incremental mindset training on undergraduate students in computer science courses that to have a greater shift in student mindsets, it is necessary to also train staff members and tutors.

Instructors' implicit theories of knowledge may also affect their expectations for student achievement. Rattan et al. (2012) performed research on 41 graduate students who were instructors or teaching assistants in math-related fields at a prestigious university. When presented with a scenario where one of their students failed the first test of the course, instructors with entity theories expected significantly lower success for the students' future achievement as a result of one test compared to instructors with incremental mindsets (Rattan et al., 2012). Alarmingly, these instructors with entity mindsets anticipated counseling students out of introductory courses in the math field to a higher degree. This clearly demonstrates the dangerous implications of educators in classrooms who hold a fixed view of intelligence.

Feedback. The feedback given to students by their teachers can also play a role in their mindset development and behaviors. Feedback practices that educators use with good intentions have been shown to have detrimental effects on students (Rattan et al., 2012). The first practice is comforting feedback. This occurs when an adult in response to a student's failure comforts the student for a perceived lack of ability (Rattan et al., 2012). Examples of comfort statements after a setback in mathematics are, "Not everybody can be good at math" or "I was not good at math either."

The use of comfort statements has also been connected to implicit theories of intelligence. Rattan et al. (2012) found that instructors who held entity theories were quicker to offer comfort to students with perceived low ability and to employ pedagogy that potentially reduced engagement compared to instructors with incremental mindsets.

These comfort statements can have negative effects on students. In a related study, Rattan et al. (2012) examined 54 undergraduate students' responses to a scenario in which they received a 65% on the first test in a calculus course. Participants were divided into three conditions based on whether the professor in the scenario provided comfort feedback, feedback that provided strategies for success, or a control in which the professor provided encouragement feedback with no comfort or strategies for improvement. Interestingly, students in the comfort feedback group perceived their professor as holding significantly lower expectations and investment than the other groups (Rattan et al., 2012, p. 735). These lower expectations from an educator can become a self-fulfilling prophecy for many students.

Another way in which educators with good intentions can give feedback that backfires is through person-directed praise, which focuses on innate abilities instead of the process or effort that a student displayed. Adults compliment childrens' abilities in the hope that it will increase their self-confidence and ultimately their performance (Ames, 1992; Dweck, 1999; Kamins & Dweck, 1999). Dweck (2010) noticed after multiple studies that students who received intelligence praise adopted a fixed mindset and were more likely to select tasks that made them look smart as opposed to tasks that they would learn from. Her conclusion was that when it is communicated to children that they will be measured by their successes, they will also measure themselves from their failures (Dweck, 1999; Kamins & Dweck, 1999). This is referred to as contingent self-worth, where the student feels valuable only after a perceived success (Dweck, 1999; Grant & Dweck, 2003).

Unfortunately, person-directed praise is very common. Over 80% of parents reported that person-directed praise was necessary to build their childrens' confidence in their intellectual abilities and to provide motivation (Dweck, 2010). While confidence is necessary, it is important for students to develop confidence not in their intelligence, but that they have the ability to learn if they apply effort and learning strategies (Dweck, 1999). Another reason for person-directed praise is self-esteem. Dweck (1999) argued that to help students have high self-esteem teachers need to be candid about what students' current skills are and what they need to do to build those skills. Adults should also offer aid to equip students with the attitudes, habits, and learning strategies necessary to succeed. Growth-minded teachers are honest with students about their abilities and provide the tools to close the gap (Dweck, 2006).

Person-directed praise has also been shown to affect students' performance. Kamins and Dweck (1999) conducted research with 64 kindergarten students role playing three success scenarios after which the children were given either person-directed praise or process-directed praise. This was followed by two scenarios in which the child made a mistake, but no feedback concerning the mistake was included in the scenario. Students in the person-directed praise group reported significantly more negative affect than the process-praise group and significantly less persistence in constructing a solution to the error in the scenario. Kamins and Dweck (1999) concluded that person-directed feedback fostered contingent self-worth in the students and invoked helpless responses. Additionally, students with contingent self-worth opted for performance-oriented tasks over mastery-oriented tasks. Feedback is necessary for students' development; however, educators must carefully examine the implicit messages sent through their feedback.

Stereotype. Another aspect of the environment is a student's perception of stereotype threat. Stereotype threat is a burden that an individual feels to confirm cultural stereotypes which limit their academic abilities and achievement (Aronson et al., 2002; Grant & Dweck, 2003). Diversity is present in every classroom that contains students. Students vary on a multitude of factors including gender, ethnicity, socio-economic status, and parental involvement. This diversity can cause individuals who perceive a threat to respond with maladaptive behaviors.

It has been shown that within the same classroom, students are treated differently (Ames, 1992). Unfortunately, some students have been treated differently due to stereotypes (Good et al., 2003). Sparks (2013) referred to this alternate treatment as a "soft bigotry of low expectations" (p. 1). At their heart, stereotypes represent entity mindset beliefs. They are erroneous knowledge structures that apply fixed abilities to certain groups of people (Anderson, 1995; Dweck, 2008).

Multiple connections have been shown between implicit theories of knowledge and stereotypes. Aronson et al. (2002) and Dweck (1999) claimed that entity theorists are quicker to stereotype than incremental theorists. This could be in part because entity theorists are fighting their own perceived stereotype of personal academic deficiency. Aronson et al. (2002) also found that stereotype targets behave similar to entity theorists when their ethnicity or gender is made salient by choosing easier, success-assuring tasks.

Stereotypes and their impact on mindsets may play a part in the under-representation of certain groups in mathematics. "A key factor driving students' intent to pursue math should be their personal sense that they belong in mathematics" (Good et al., 2012, p. 700). Students who identify with groups that have negative mathematical stereotypes may face obstacles. Aronson et al. (2002) claimed that a perceived stereotype could be strong enough to sway a student's implicit beliefs of intelligence.

A persistent stereotype in the mathematics community is that males are more capable of mathematical thinking and quantitative reasoning than females. Many who hold this stereotype point to discrepancies on standardized tests such as the reported 35 point lag that females exhibit on the math section of the SAT (Good et al., 2003). Is this achievement deficiency evidence of lesser ability or of females' perception of stereotyping and their environment? Evidence is mounting regarding the role that mindsets play in the underrepresentation and underachievement of women in mathematics (Dweck, 2008). Good, Rattan and Dweck (2012) attribute females' underperformance in mathematics to two subtle messages in their environments: the first is that mathematical ability is fixed, and the second is the stereotype that women possess less of this ability than men, concluding that these messages "work together to erode women's, but not men's, sense that they belong in math and, hence, their desire to pursue math in the future" (p. 700).

While evidence exists of females lagging behind males in mathematics achievement, there is also evidence that females can surpass males. Lloyd, Walsh, and Yailagh (2005) noted in a Canadian study of fourth- and seventh-grade students that girls' mathematical achievement on standardized tests and course grades were similar, if not higher, than the boys in the study. Of note was the finding that females were more likely to be under-confident toward mathematics achievement and to attribute failures to lack of assistance from their teacher than males. This provides evidence of possible stereotyping from teachers regarding assistance in mathematics.

Fortunately, there is evidence that training in an incremental mindset can help females counter the negative effects of stereotypes. Good et al. (2003) conducted a study in which college students mentored seventh-grade students who were at-risk of stereotype threat. Students were divided into four groups. The first group received mentoring that encouraged a growth mindset, the second group received mentoring concerning the transition to middle school, and the third group received both the growth mindset and transition mentoring. The final group received an anti-drug message and served as a control for the experiment. At the end of the school year, females trained in the incremental mindset received significantly higher scores on a standardized math test (Good et al., 2003). Additionally, girls showed greater gains than boys and decreased the achievement gap. This finding supports Dweck's (2008) conclusion that females with growth mindsets are less at risk of negative effects from stereotypes.

Females have been historically under-represented in mathematics fields (Dweck, 2008). Classroom environments that communicate an incremental view of mathematics are an important first step toward increasing the representation and achievement of females in mathematics and science (Good et al., 2012). Good et al. (2012) conjecture that females' disengagement with mathematics may result not from a disinclination, but from a decreased sense of belonging. She conducted a large study of undergraduate students in a calculus course and found that the perception of an entity-oriented environment and of a stereotyping environment were significant predictors of a sense of belonging for females. While the focus of the study was on females' sense of belonging and achievement in mathematics, the findings are applicable to any member of a stereotyped group that receives messages of academic deficiency. Fortunately, an incremental mindset can help stereotyped individuals counteract the effects of stereotype and foster a sense of belonging.

Mindset Critiques

Similar to this literature review, the bulk of current research discusses implicit theories of intelligence in a favorable light and has found positive results with training. In an effort to provide a comprehensive review of the literature, it is imperative that criticisms toward these implicit theories of intelligence also be examined. Donohoe et al. (2012) offered the most critiques, questioning if it is possible to make a large difference in mindset with only brief interventions. They, along with Blackwell et al. (2007), raised concerns about the longevity of the positive effects of implicit theory interventions.

Some conflicting evidence has also arisen regarding the connection between mindset and academic achievement (Blackwell et al., 2007). Furnham, Chamorro-Premuzic, and McDougall (2002) found evidence in a British study of college students that students' mindsets were not related to achievement, but to their personality. One reason for this contradictory finding may be explained in light of criticism by Kristjansson (2008) of Dweck's theories of intelligence questionnaires. Kristjansson's (2008) criticism focused on the "strict dichotomy" implicit in the various questionnaires which "seem to be so tailored as to catch within their net exaggeratedly divisive answers" (p. 225). He argued that individuals rarely fit neatly into two distinct categories. As a result of this criticism, the data analysis will not include individuals whose responses are ambiguous, but only those who are clearly identified with a specific mindset.

Summary

This literature review has provided a comprehensive examination of important research on cognitive learning theory regarding implicit theories of knowledge, particularly related to mindset. This review provides a backdrop against which the present study can be understood.

One implication of the relative youth of mindset research is the small number of studies focused specifically on college students and mathematics. Due to this shortfall, it was necessary to use research from both K-12 and college settings to construct a comprehensive literature review. A summary of the research included in this literature review related to K-12 education is given, followed by a summary of research on undergraduate students.

Research with K-12 students showed that patterns associated with entity mindsets were observed in students as young as seven years old and kindergartners demonstrated different responses to person-directed and process-directed praise and patterns associated with (Heyman & Dweck, 1998; Kamins & Dweck, 1999). Another focus of K-12 studies was the persistence of students demonstrated by the connection between entity mindsets and helpless responses, as well as the connection between incremental mindsets and mastery-oriented responses (Dweck & Leggett, 1988; Elliott & Dweck, 1988). The importance of middle school students' perceptions of control regarding their failures and successes was noted along with a key study that demonstrated the importance of incremental mindsets for achievement in mathematics (Banks & Woolfson, 2008; Blackwell et al., 2007). One response to the growing research on implicit theories of intelligence for K-12 students was inclusion by one textbook publisher of an opening chapter on mindsets and neuroplasticity (Sparks, 2013).

Key findings regarding college-level students included connections between students' mindsets and their attitudes, goal setting, self-esteem, self-worth, achievements, and even their response to depression (Dweck, 1999; Grant & Dweck, 2003; Kim & Kellert, 2010; Robins & Pals, 2002; Zhao et al., 1998). College students who held fixed mindsets believed that high intelligence guaranteed flawless performances and when faced with obstacles were more likely to exhibit helpless responses, decreased learning strategy selection, and physiological changes (Dweck, 2010; Mangels et al., 2006; Nussbaum & Dweck, 2008). Rattan et al. (2012) found that it was possible to briefly manipulate undergraduates' view of intelligence through the simple task of reading an article while Aronson et al. (2002) showed that training in incremental mindsets improved students' semester grade point averages.

While some research related to mindset and mathematics learning has been completed, no studies were found that focused specifically on the learning of statistics at the college level. As a relatively new cognitive construct of learning, 'mindset' has been most frequently researched by Dweck and colleagues. Based on the critiques of the literature, an independent study of the connection between mindset and academic achievement is warranted.

The chapter began with an examination of the landscape in statistics education and moved into cognitive learning theory. Similar to its historical introduction, attribution theory preceded the discussion of mindset theory. The chapter then switched to focus on research on the effectiveness of training individual's attributions or mindsets.

Specific topics that have received attention connected to mindset training were examined including the educational environment and the demographic characteristics of the learner. The chapter closed with an examination of critiques toward mindset theory.

CHAPTER 3

Methodology

Chapter 3 provides an examination of the methods and procedures used to guide this study. A quasi-experimental, pretest-posttest, nonequivalent control group design was implemented in this quantitative research. The population, sample, sampling design, instrumentation, and treatment are described in this chapter. Additionally, data collection and analysis are outlined along with limitations and necessary resources to carry out the research.

This research examined the effects of mindset and an intervention of incremental mindset training in an introductory statistics college course on student attitudes toward statistics and student mastery of statistical content. The subjects were students at a small faith-based, liberal arts college. The study sought evidence among these students of a difference in attitudes toward or mastery of statistics based on their initial mathematics mindset. An additional aspect of the study was an examination of the difference that incremental mindset training had on these same variables of attitudes and mastery. The study employed historical data where previous class sections of statistics served as the control and the fall 2014 sections implemented the treatment of incremental mindset training.

Review of Related Literature and Research

The review of relevant literature regarding implicit theories of knowledge was conducted through two libraries: the Hulst Library located on the campus of Dordt College and the I. D. Weeks Library located on the campus of the University of South Dakota. The Hulst Library assisted with inter-library loan requests for books and the I.

D. Weeks library assisted with inter-library loan requests for articles. The searches were conducted through Ebscohost databases. Initially, resources were located by subject and keyword searches. Through these initial resources, an additional search technique was implemented of locating articles and books that were referenced or referred to multiple times by the research.

Population

The population for this study was undergraduate students at a small, faith-based, liberal arts college in the Midwest. Fall enrollment for the college has remained at approximately 1,400 students for the past five years. The students who made up this population were predominately Caucasian and of traditional college age with 95% of students between 18 and 25 years of age and 7.7% of students identified as minorities. The average ACT for incoming students in the fall 2011 through fall 2014 academic semesters was 24.5. The gender breakdown for the college was evenly balanced with males comprising 52.4% of students and females the remaining 47.6%. The education major had the largest enrollment for the college, followed by students majoring in business administration, engineering, agriculture, and nursing.

Sample

The sample for this study was all students who completed pretest and posttest assessments in the 12 introductory statistics classes between August 2011 and December 2014, with the two sections in the fall 2014 semester receiving the treatment. While the sample was not randomly selected, the researcher assumes that it was representative of students who enrolled in introductory statistics. The sample had similar average ACT scores ($\bar{x}$ = 25.1) and grade point averages ($\bar{x}$ = 3.30). The gender breakdown also mirrored the population with 51.4% males and 48.6% females.

The course description for this class as found in the college catalog follows:

> An elementary course in statistical techniques and methods and their application to a variety of fields. Topics include data analysis, design of experiments, and statistical inference including confidence intervals and hypothesis testing. Spreadsheet knowledge is suggested. Prerequisite: an ACT mathematics score of 22 or higher or satisfactory completion of Mathematics 100, 106 or 118 (Dordt College, 2013, p. 131).

The prerequisite requirements ensured that students had the mathematical skills necessary to be successful in this class.

Statistics enrollment at this institution has mirrored the national growth; class enrollments increased from 105 students in 2005 to 188 students in 2014 as shown in Figure 1. Students enrolled in this course represent a diverse set of interests, abilities, and backgrounds. A small percentage of students who take this course are interested in pursuing statistics further as it is a requirement for a statistics, mathematics, or actuarial science minor or major. Another minority group of students takes introductory statistics as preparation for graduate school. The final two groups of students represent at least 80% of students. The first group includes students who use introductory statistics to meet the quantitative literacy graduation requirement. The final group is students required to take the course for their major. Majors that require introductory statistics include biology, business administration, computer science, education, psychology, and sociology. Given the diverse backgrounds and motivations for taking introductory statistics, it follows that the level of the students also varies from freshman through seniors.

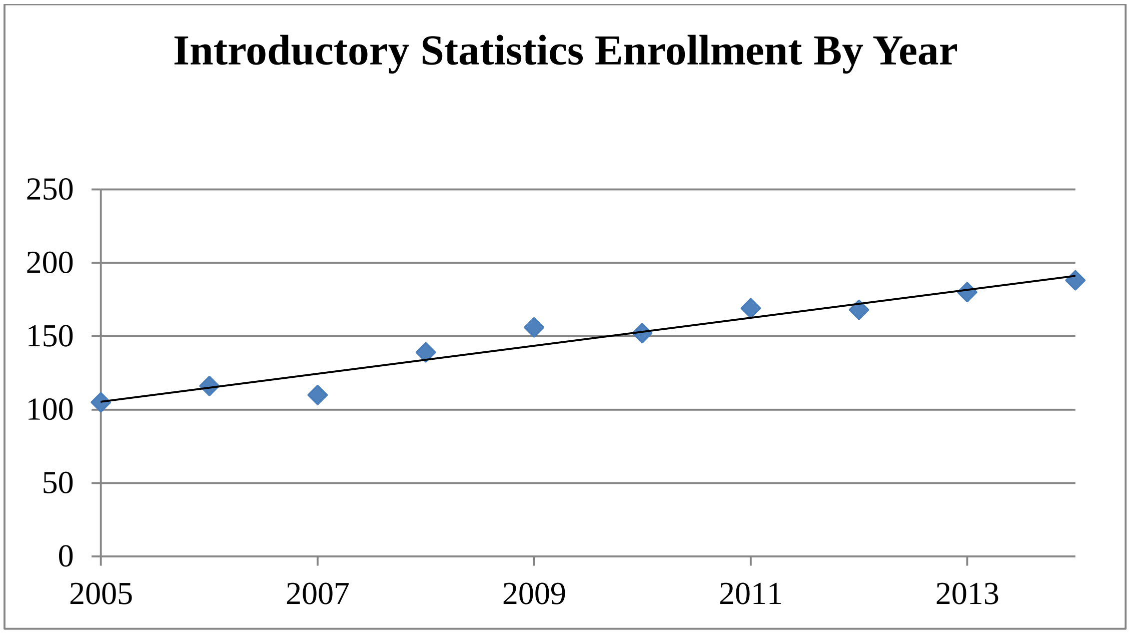

Figure 1. Enrollment in Introductory Statistics. This figure illustrates the increased enrollment at the institution under examination.

The control group was 490 students in 15 class sections with an additional 57 students in the two class sections that comprised the treatment group for a total sample size of 547. The course enrollment and the number of students who completed all aspects of the treatments and assessments determined the actual number of students. In past semesters, 80-90% of students completed all assessments. There is no evidence that completers differ from non-completers demographically. While the number of students who did not complete all assessments is small, this group does not seem to over-represent any demographic including gender, ethnic background, grade-level, academic ability, or intended major.

Sampling Design

This study employed quasi-experimental methods and made use of a pretest-posttest, control group design. The research was quasi-experimental since a treatment was applied, but the sample was not randomly selected and the treatment was not randomly assigned. The sample consisted of students who enrolled in introductory statistics in the semesters under examination. Additionally, students who received the treatment were not randomly selected, but the result of students who enrolled in all sections of introductory statistics in the fall of 2014. While experimental methods were employed, the study also included an element of ex post facto design, as data from previous introductory statistics courses generated the control group for research questions two and three.

Instrumentation

Three instruments were used to assess each student's attitude toward statistics, mastery of statistical knowledge, and theory of intelligence. The Student Attitudes Towards Statistics – 36© (SATS), CAOS, and Theories of Math Intelligence Scale –Self Form (TMIS) (Dweck, n. d.) instruments were implemented at both the beginning and the end of the course. All instruments were implemented on the treatment group, but only the SATS© and CAOS were used for the control group. Since each of the instruments was pre-existing with established reliability and validity, a pilot study was not conducted.

Students' attitudes toward statistics were assessed through the SATS© assessment (See Appendices A and B). This 36-item online instrument provided a valid representation of students' attitudes regarding statistics. Each item required a response on a seven-point Likert scale. Responses were grouped into six components of attitude:

affect, cognitive competence, value, difficulty, interest, and effort. The SATS© includes a version for use at the beginning (pre-SATS©) and at the end of the semester (post-SATS©). This instrument has been confirmed as a valid measure of attitudes toward statistics (Nolan et al., 2012). Internal consistency for all components of the SATS© is within the acceptable range (i.e. Cronbach's alpha coefficients between .66 and .85) for single administrations (Nolan et al., 2012).

The SATS© was originally selected for use in conjunction with research of the curriculum being developed because of its reliability, validity, and familiarity to the researcher. The SATS© suited the present research well since it assessed multiple measures of attitude giving a picture of the complexity of students attitudes. The availability of historical data concerning attitudes using the SATS© was also a factor in its selection.

The CAOS was administered online to assess students' mastery of statistics at both the beginning and at the end of the semester. This assessment was designed to focus on conceptual understanding as opposed to procedural knowledge and computation. The focus of the instrument is reasoning about variability. The 40 items on the CAOS posttest are reliable, producing a Cronbach's alpha coefficient of .77 (delMas, Garfield, Ooms, & Chance, 2007). The validity for the CAOS as a measure of important basic learning outcomes in statistics was established unanimously by a set of 18 expert raters (delMas et al., 2007). The CAOS was a good fit for this research because of its focus on conceptual understanding. It goes beyond testing students' memories of terminology to their deeper understandings of statistics.

The instrument to assess mindset toward mathematics was the TMIS (Dweck, n. d.). This is an unpublished instrument that Dweck adapted from the Theories of Intelligence Scale (Dweck, 1999) to specifically focus on mathematics. The choice of a domain-specific instrument was made following the suggestion of Calisto (2013) in his research exploring malleability primes in mathematics classes. The instrument (see Appendices C and D) consists of four questions using a six-point Likert-scale. The scale has high internal reliability (i.e. Cronbach's alpha ranging from .94 to .98) with a test-retest reliability of .8 over a two-week interval (Dweck, Chiu, & Hong, 1995). The scale also validly discriminates against other measures since it was not correlated with self-esteem, self-presentation, cognition, or motivation. The adaptation to a mathematics-specific focus also increased the validity of the instrument as a measure of a student's mathematical mindset.

Treatment

The incremental mindset treatment was designed using materials and findings from successful interventions in the literature review. The treatment consisted of four incremental mindset-training sessions throughout the fall 2014 semester. Cutts (2008) employed a similar design of four 10 to 15-minute sessions that was shown successful for introductory computer science classes at Glasgow University. The goal of the sessions was to help students understand how the brain functions biologically with a focus on the malleability of intelligence. In this study, each of the four 15-minute training sessions was implemented approximately three weeks apart. Each session occurred during class time and was led by the researcher to ensure consistency. Verbal permission to conduct the trainings was granted by the professor responsible for teaching each of the introductory statistics.

A number of approaches to both attribution retraining and mindset training have successfully been employed to alter students' mental constructs. Attribution retraining helps students cope with setbacks by attributing their failures to inadequate effort, rather than a lack of ability. Both attribution retraining and mindset training have employed the use of videos (Boese et al., 2013), reading activities (Kim & Kellert, 2010), writing activities (Aronson et al., 2002; Hall et al., 2004), and computer-assisted instruction (Donohoe et al., 2012). In his study of attribution retraining, Robertson (2000, p. 118) found that no single medium was more effective than others. Given this finding, multiple approaches were implemented in an effort to differentiate the treatment delivery and connect with students in different methods. A question was also included in the post-test assessment of the TMIS that asked students to rank the effectiveness of the four treatments at the close of the semester.

The design of the sessions was adapted from the research of Berkeley et al. (2011), Boese et al. (2013), Burk (2011), Cutts (2008), Hall et al. (2004), and Sriram (2010). The design implemented combinations of a brief video, article, presentation, or activity introducing concepts in incremental theory including mindsets, the physiology of the brain, response to feedback, goals, and the role of effort. Following the success that Robertson (2000) found when combining strategy instruction with reattribution training, students were also given guidance in the sessions on successful techniques for mastering statistics. Dweck supported this approach with the rationale that telling a student to try harder is not enough without providing strategies to do so (Sparks, 2013). Students in the treatment were given guidance throughout the semester on how to respond to challenges and negative feedback in the course. They were also directed to resources to help improve their mastery of the material including online material and tutoring available free of charge in the Academic Skills Center.

Similar to attribution retraining, a consolidation activity (see Appendix E) closed each treatment to help students personalize the new information they received (Hall et al., 2004). The consolidation took the form of a small group discussion or an individual writing task. The focus of each of the sessions is outlined in Figure 2; more detail is given in Appendices E - G.

Session	Topics	Activity Type	Consolidation
1	Fixed and Growth Mindsets Brain Physiology	Presentation Reading	Discussion
2	Response to Feedback Helplessness and Mastery Responses	Card Sort Activity Presentation Thought Questions Video	Written Reflection
3	Performance and Learning Goals Set Course Goals	Video Presentation	Written Reflection
4	Mindsets in Role Models The Role of Effort	Presentation Video	Written Reflection

Figure 2. Treatment outline. An outline of each incremental mindset training session.

Data Collection

The SATS©, CAOS, and TMIS instruments were administered online, outside of class during the first week of class and again during the last week of class for the fall 2014 semester. The CAOS assessments had been regular requirements of introductory statistics classes for the institution since the fall of 2011 in conjunction with a grant for the National Science Foundation. Similarly, the SATS© assessments had been regularly assessed since fall of 2013 in conjunction with a grant for the National Science Foundation.

It was hypothesized that students who received the treatment would experience the benefits of increased tendencies towards growth mindsets, improved attitudes toward statistics, and increased academic achievement. Students who completed, at minimum, the initial opt-out screen of all pre-assessments (see Appendices K and L) received credit for a daily assignment. Similarly, students who completed, at minimum, the initial opt-out assessments received credit for a daily assignment. While students have been allowed to opt-out after the initial screen and still receive full credit in previous implementations, student participation rates for the SATS© and CAOS assessments has been over 85% in prior semesters. For the fall 2014 semester, the four question TMIS was also required in addition to the SATS© and CAOS to receive credit equivalent to a daily assignment grade.

The procedure for conducting the assessments ensured that students received the information and had adequate time to complete them. Students were introduced to the assessments during the first class period by the class instructor. After class on the first day, all students received an e-mail invitation (see Appendix H) with links to the assessments and a brief explanation of the purpose and procedures of the study. Each assessment was run through Survey Monkey™ and remained open for one week. A reminder e-mail was sent one day before the assessments closed. Special invitations were sent to any students who added the class after the first day of class. A similar process occurred with the posttest for each of the three instruments. Students were informed during the last week of class and received an e-mail with survey links. A reminder e-mail was sent one day prior to the close of the instruments.

To ensure that all individuals responsible for or affected by this research were informed and protected, appropriate permissions and reviews were completed prior to data collection. Permission to conduct this research was granted from the Area Leader of the Mathematics, Statistics, and Computer Science department (see Appendix I), and the head of the Statistics Department (see Appendix J). Permission to use existing CAOS and SATS© data from an ongoing National Science Foundation study was granted from the principal investigator of the project (see Appendix J). Permission to conduct this research was secured from the Institutional Research Board for the college during the spring 2014 semester. Students were assured of the confidentiality of their responses in the invitation to the instruments. Student data were anonymous to the researcher as a departmental assistant assigned each subject an identification number. The assistant also matched each student's pretest-posttest results. Informed consent was given through an initial opt-out screen for each assessment (see Appendices K and L). This informed students and ensured that they had the opportunity to not participate if they were uncomfortable with an assessment.

Data Analysis

Robust data analysis procedures were used throughout this research which combined both pre-existing and experimental data. The Statistical Procedures for Social Sciences software (IBM SPSS Statistics Version 22 for Windows) was used to conduct all statistical analysis. A software application called G*Power, developed by Faul, Erdfelder, Buchner, and Lang (2009) assisted in the power analyses. The online submission of all instruments through SurveyMonkey™ created spreadsheets that were converted to SPSS documents. Prior to any analysis, thorough data screening was employed to ensure that no outliers distorted the data and subsequent analyses. The threshold to determine and remove univariate outliers was observations beyond five standard deviations of the sample mean (Schweinle, 2013). The threshold to determine and remove bivariate outliers was observations that violated three or more diagnostic measures.

Appropriate statistical analysis was employed to address each of the research questions. An alpha level of .05 was used for all tests with the exception of situations that employed multiple comparisons in which case a Bonferroni correction was applied.

Analyses of covariance (ANCOVA) was used for questions one through four and *t* tests for question five. ANCOVA is a statistical analysis that assesses group differences on means for a continuous dependent variable while controlling for differences in a covariate (Warner, 2013).

A measure of effect size was calculated for all analyses using the software program G*Power (Faul et al., 2009). Effect size is an index of "the magnitude of the differences between means" which is independent of sample size and displayed in unit-free terms (Warner, 2013). Using Cohen's (1988) index guidelines, large effect sizes represented measures of .4 and greater, medium effects between .25 and .4 and small effect sizes between .1 and .25.

Each student was classified as exhibiting either an entity or incremental theory toward mathematics based on the results of the TMIS. Following the research of Mangels et al. (2006), students whose average scores were unambiguous (entity: ≤ 3, incremental: ≥ 4) were eligible for the study. Dweck (2008) estimated that approximately 40% of students were classified as holding entity mindsets, 40% with incremental mindsets and the remaining 20% of students were not consistent enough in their response to be classified as holding either theory. Students in this 'inconsistent' category were not included in the analyses. While removing students whose TMIS scores were inconsistent decreases the sample size and consequently the power, the tradeoff was that it more clearly distinguished between the entity and incremental mindsets. The data analysis for each of the five research questions follows.

1. What differences exist in students' attitudes toward statistics based on their initial mindset toward mathematics?

ANCOVA was used to assess if there were differences between students' initial mathematics mindsets and the components of their attitudes toward statistics since these tests statistically control for differences on initial attitudes toward statistics between mindset groups. The independent variable of students' initial mathematics mindset was examined categorically as either an entity or incremental mindset. The dependent variable was each component of the adjusted posttest SATS© score. The ANCOVAs assessed group differences between mathematical mindsets for the continuous variable SATS© posttest score while controlling for the SATS© pretest score.

2. What differences exist in students' attitudes toward statistics between those who did and did not receive incremental mindset training?

The dependent variable for this research question was each component of the adjusted posttest SATS© score. The independent variable was the students' group: control or treatment. The control for this research question was students' SATS© scores in previous semesters while the treatment was SATS© scores of students enrolled in statistics during the fall 2014 semester. ANCOVA was used to assess if there were differences between students who received incremental mindset training and those who did not regarding their attitudes toward statistics since these tests statistically control for differences on initial attitudes toward statistics.

3. What differences exist in students' acquisition of statistical knowledge between those who did and did not receive incremental mindset training?

The independent variable for this analysis was the student's group: control or treatment. The dependent variable was the posttest CAOS assessment score. An ANCOVA was used to reduce the effects of the initial group differences on the pretest CAOS instrument. The ANCOVA examined if differences existed in students' acquisition of statistical knowledge between the control and treatment group while statistically controlling for the covariate of pretest CAOS score.

4. What differences exist between students' initial mathematical mindset and their change in statistical knowledge throughout an introductory statistics course?

ANCOVA was used to assess if there were differences between students' initial mathematics mindsets and the knowledge gained as assessed by the CAOS instrument since this test statistically controls for differences of initial statistical knowledge between mindset groups. The independent variable in this assessment was the student's pretest TMIS score recorded as a categorical variable. The covariate was the level of statistical knowledge as assessed by the CAOS pretest instrument and the dependent variable was the posttest CAOS instrument. The ANCOVA assessed group differences between mathematical mindsets for the continuous variable posttest CAOS scores while controlling for the pretest CAOS score.

If the assumptions for ANCOVA were not met for research questions one through four, *t* tests were used according to guidelines given by Wright (2006) and Weinfurt (2000). As a result of the multiple comparisons, a Bonferroni correction was used. The corrected alpha level of .008 was necessary to show statistical significance for component level *t* tests. An a priori examination indicates adequate power to detect large effect sizes with the ANCOVA *F* test ($d = .4$, $1\text{-}\beta = .8$, $N = 52$) and with the component level *t* tests ($d = .8$, $1\text{-}\beta = .8$, $N = 42$) (Faul et al., 2009).

5. What differences exist by gender in the change of students' attitudes toward statistics for students who received training in an incremental mindset?

The dependent variables for this research question were the components of the SATS© change score, which represented the change for each component of a student's SATS© score from the pretest to the posttest. The independent variable was the student's gender: male or female. A *t* test was used to assess if differences in attitudes existed between the two genders by examining the mean component SATS© change score for males and females. As a result of the multiple comparisons, a Bonferroni correction implies an alpha level of .008 to show statistical significance. An a priori power analyses indicated adequate power to detect medium to large effects with *t* tests (n_1 = 30, n_2 = 30, d = .65, 1-β = .80) (Faul et al., 2009).

Resources

The resources necessary to conduct this research were readily available. Finances were not a factor in carrying out the proposed project since all survey instruments were available free of charge. Permission to use the instruments was granted for the CAOS, TMIS, and SATS© (see Appendices M - O). While this study included data for seven semesters, time was not an issue since much of the data had already been collected for previous studies. The appropriate permissions were granted to use data from prior semesters and conduct the research (see Appendices I and J). Additionally permission to use the research design was granted from Cutts, a professor who employed a similar study in computer science classes at The University of Glasgow (see Appendix P). Institutional Review Board (IRB) approvals were obtained prior to data collection commenced for both the host school (see Appendix Q) and the sponsor university for which this research was submitted (see Appendix R).

Summary

Chapter 3 has outlined the methodology that was employed in the research of mindsets, attitudes toward statistics, and mastery of statistical concepts. The population, sample, and sampling design were discussed as well as the instrumentation, treatment, and data collection procedures. Additionally, the data analysis and power analysis for each research question were outlined. The chapter closed outlining necessary resources to carry out the study.

CHAPTER 4

Findings

Chapter 4 focuses on the findings and results of the effects of mindset and an intervention of incremental mindset training in a college introductory statistics course. Areas examined included student attitudes toward statistics and student mastery of statistical content. The chapter opens with an examination of the response rate and specific sample demographics. The chapter then explores particular findings for each of the five research questions:

1. What differences exist in students' attitudes toward statistics based on their initial mindset toward mathematics?
2. What differences exist in students' attitudes toward statistics between those who did and did not receive incremental mindset training?
3. What differences exist in student's acquisition of statistical knowledge between those who did and did not receive incremental mindset training?
4. What differences exist between students' initial mathematical mindset and their change in statistical knowledge throughout an introductory statistics course?
5. What differences exist by gender in the change in students' attitudes toward statistics for students who received training in an incremental mindset?

Response Rate

The treatment group of students in the fall 2014 introductory statistics course consisted of the 57 students enrolled in the course. The response rate for the pretest assessments was 96.1%. Throughout the semester, five students dropped the course. An additional 22 students either opted out of completing one or more assessments, or declined the use of their responses for research purposes. The result was 30 students who completed both the pretest and posttest SATS©, and CAOS assessments producing a response rate of 57.7% for students in the treatment group. All but one of these students also completed both the pretest and posttest TMIS assessment resulting in a drop of a pretest response rate of 96.1% to 55.8% for the posttest TMIS.

The historical data regarding student attitudes towards statistics included 30 students in the treatment group and 111 students in the control group for a total of 141 students. The population of students in both the treatment and control group which implemented the SATS© assessment consisted of 234 students producing a response rate of 47.4%.

The CAOS assessment was implemented in the fall 2011 through fall 2014 semesters to 547 students. A total of 411 students completed the pretest and posttest CAOS assessment resulting in a response rate of 75.1%.

Demographic Data

The students in the sample were representative of the population on gender, academic achievement, and college majors. The gender breakdown of students enrolled in introductory statistics was nearly even with 48.6% females and 51.4% males. The average composite ACT score was 25.3 with an average Math ACT score of 25.2. According to the Institutional Research Department, the mean high school grade point average of the sample was 3.57 and 3.30 for the college grade point average. The largest representation of student majors came from business administration, followed by education, nursing, social work, and agriculture. Engineering is a large major for the college, but was not well represented in this sample since statistics is not a required course for the major. The students in the treatment group shared similar demographics with 46.6% females and 53.4% males, an average composite ACT score of 25.1 and an average math ACT of 24.4. The average high school grade point average and college grade point average were 3.53 and 3.25 respectively. The largest majors for the treatment group were business administration and education, followed by agriculture and biology.

Results

Attitude differences based on mindset. (Research Question 1: What differences exist in students' attitudes toward statistics based on their initial mindset toward mathematics?) Minimal differences were present in students' attitudes towards statistics by mindset categories. Table 1 represents the means and standard deviations, as well as the sample size for each component of the SATS©.

Table 1

Mean SATS© Gain Score by Mindset Category

	TMIS Category	*N*	*M*	*SD*
Affect	Fixed	4	-0.375	0.875
	Growth	23	0.378	0.976
Cognitive Competence	Fixed	4	0.042	0.370
	Growth	23	0.0348	0.601
Difficulty	Fixed	4	0.000	0.583
	Growth	23	0.184	0.667
Effort	Fixed	4	-0.625	0.361
	Growth	23	-1.304	0.205
Interest	Fixed	4	-0.875	0.479
	Growth	23	-0.424	0.915
Value	Fixed	4	0.083	1.086
	Growth	23	-0.009	0.839

A summary of the data analysis for research question one is shown in Table 2. The sample size violated the assumptions necessary to perform an ANCOVA, therefore, multiple *t* tests were used according to guidelines given by Wright (2006) and Weinfurt (2000). No significant differences were found based on students' initial mindsets towards mathematics. The lower than expected response rate and low percentage of students categorized with an entity mindset negatively affected the power to detect differences in students' attitudes towards statistics resulting in a post hoc power analysis of ($d = .8$, $1-\beta = .30$, $N_1 = 4$, $N_2 = 23$) (Faul et al., 2009).

Table 2

Comparison of Mean SATS© Gain Score by Mindsets Category

	t value	*df*	Probability	*M*
Affect	-1.439	25	.163	-0.752
Cognitive Competence	0.022	25	.983	0.007
Difficulty	-0.516	25	.610	-0.184
Effort	1.310	25	.202	0.679
Interest	-0.952	25	.350	-0.451
Value	0.196	25	.846	0.093

* *M* represents the mean fixed mindset gain score subtracted from the mean growth mindset gain score.

Attitude differences based on mindset training. (Research Question 2: What differences exist in students' attitudes toward statistics between those who did and did not receive incremental mindset training?) The mean for each of the posttest SATS© components by treatment group is depicted in Table 3. The attitude component of difficulty received the lowest average response in both groups ($\mu_N = 3.759$, $\mu_Y = 3.774$), while effort received the highest ($\mu_N = 5.635$, $\mu_Y = 5.219$).

Table 3

Mean Posttest SATS© Scores by Treatment Group

	Treatment	*N*	*M*	*SD*
Affect	N	111	4.002	1.282
	Y	30	4.467	1.091
Cognitive Competence	N	111	4.868	1.039
	Y	30	4.894	0.522
Difficulty	N	111	3.759	0.777
	Y	30	3.774	0.790
Effort	N	111	5.635	0.930
	Y	30	5.219	1.160
Interest	N	111	4.288	1.156
	Y	30	4.167	1.158
Value	N	111	4.819	0.869
	Y	30	5.032	0.915

* N = No Treatment; Y = Received Treatment

An ANCOVA was used to assess statistical significance for each of component of the posttest SATS© while controlling for the pretest SATS© results by treatment group as shown in Table 4. The components of affect, cognitive competence, difficulty, interest, and value did not demonstrate a statistically significant difference between the control and treatment groups. The component of effort produced a statistically significant result, $F(1, 138) = 14.778$, $MSE = 10.954$, $p < .001$ with the treatment group dropping in their effort expended at a statistically significant greater rate than the drop present in the control group. The effort component measured the amount of work the student expended to learn statistics. A post hoc examination of power indicated adequate power to detect medium effects with the ANCOVA *F* test ($d = .25$, $1\text{-}\beta = .83$, $df_1=1$, $df_2=138$, $N = 139$) (Faul et al., 2009).

Table 4

Comparison of Mean Posttest SATS© Scores by Treatment Group

	Y (*n* = 30)	N (*n* = 111)	*F* value	Probability
Affect	4.467	4.002	3.336	.070
Cognitive Competence	4.894	4.868	0.709	.401
Difficulty	3.774	3.759	0.085	.771
Effort	5.219	5.635	14.778	.000*
Interest	4.167	4.288	0.007	.932
Value	5.032	4.819	2.145	.145

* denotes significant difference at .008

* N = No Treatment; Y = Received Treatment

Statistical knowledge differences based on mindset training. (Research Question 3: What differences exist in students' acquisition of statistical knowledge between those who did and did not receive incremental mindset training?) The CAOS was used to assess students' knowledge of statistical concepts. Figure 3 demonstrates the longitudinal changes in students' pretest and posttest scores as well as the gains demonstrated.

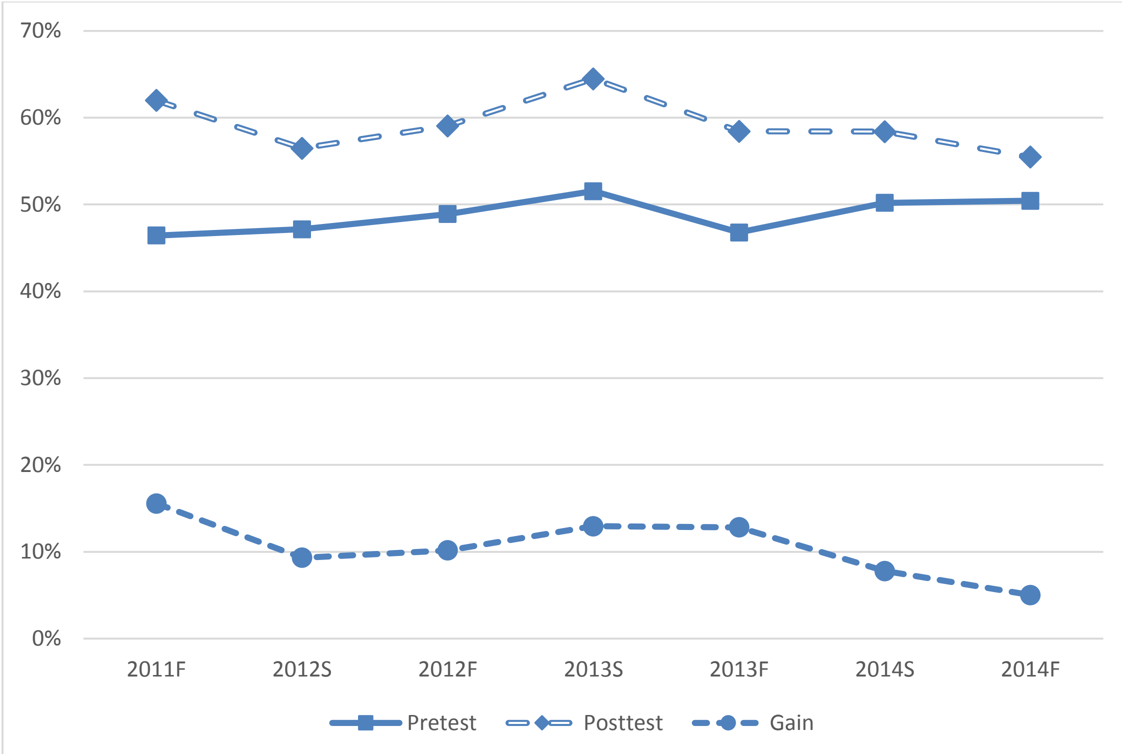

Figure 3. CAOS Trend lines. A historical description of the pretest, posttest, and gain scores for the CAOS assessment.

Students in the control group had on average a higher percentage of questions correct on the posttest CAOS instrument ($\mu_N = .598$, $\mu_Y = .555$). The results of the pretest CAOS instrument were similar across groups as can be seen in Table 5.

Table 5

Mean Pretest and Posttest CAOS Scores by Treatment Group

	Treatment	*N*	*M*	*SD*
CAOS-Pre	N	381	0.487	0.121
	Y	30	0.504	0.091
CAOS-Post	N	381	0.598	0.142
	Y	30	0.555	0.121

* N = No Treatment; Y = Received Treatment

An ANCOVA was used to assess if there were differences between the control and treatment group on their posttest CAOS results while controlling for the pretest CAOS score. Table 6 demonstrates statistical significance of the difference between the control and treatment group on the amount of knowledge gained, $F(1, 408) = 5.860$, $MSE = .082$, $p = .016$, with the control group showing significantly more knowledge gained.

Table 6

Comparison of Mean Posttest CAOS Scores by Treatment Group

	Y (n = 30)	N (n = 381)	*MSE*	*F* value	Probability
CAOS	.555	.598	0.082	5.860	.016*

* denotes significant difference at .05

* N = No Treatment; Y = Received Treatment

Statistical knowledge gains based on mindset. (Research Question 4: What differences exist between students' initial mathematical mindset and their change in statistical knowledge throughout an introductory statistics course?) Table 7 demonstrates the pretest and posttest scores for students categorized by mindsets. Students categorized with fixed and growth mindsets, as well as students with ambiguous mindsets, all held similar pretest CAOS scores. Students with ambiguous mindsets gained the most on the posttest CAOS, followed by students with growth mindsets.

Table 7

Mean Pretest and Posttest CAOS Scores by Mindset Category

	TMIS Category	*N*	*M*	*SD*
	Fixed	4	0.515	0.091
CAOS-pre	Growth	23	0.510	0.097
	Ambiguous	2	0.523	0.074
	Fixed	4	0.493	0.135
CAOS-post	Growth	23	0.553	0.120
	Ambiguous	2	0.686	0.040

The sample size necessary to perform an ANCOVA analysis was not met; therefore, a *t* test was used to compare the CAOS difference scores by mindset category. Table 8 summarizes the results. No significant differences were found based on students' initial mindsets towards mathematics. The lower than expected response rate and low percentage of students categorized with an entity mindset negatively affected the power to detect differences in students' attitudes towards statistics resulting in a post hoc power analysis of (d = .8, 1- β = .30, N_1 = 4, N_2 = 23) (Faul et al., 2009).

Table 8

Comparison of Mean CAOS Gain Score by Mindset Category

	t value	*df*	Probability	*M*
CAOS	-0.889	25	.224	-0.754

* *M* represents the mean CAOS gain score for students categorized with a growth mindset subtracted from the mean gain score for students categorized with a fixed mindset.

Attitude differences by gender. (Research Question 5: What differences exist by gender in the change in students' attitudes toward statistics for students who received training in an incremental mindset?) Among students who received the mindset training treatment, attitudes towards statistics varied by gender. Table 9 demonstrates the gender differences. Both males and females gained the most on the component affect and lost the most for the component effort, although the genders gained and lost at different rates.

Table 9

Mean SATS© Gain Scores by Gender

	Treatment	*N*	*M*	*SD*
Affect	F	16	0.583	1.002
	M	14	0.155	1.045
Cognitive Competence	F	16	0.260	0.537
	M	14	-0.169	0.566
Difficulty	F	16	0.286	0.506
	M	14	0.016	0.774
Effort	F	16	-0.875	0.780
	M	14	-1.536	1.031
Interest	F	16	-0.234	0.946
	M	14	-0.750	0.766
Value	F	16	0.361	0.631
	M	14	-0.467	0.821

Differences in the mean change among males and females in their attitudes toward statistics were present as is shown in Table 10. While there were differences present by gender for change in the components of cognitive competence (μ_M = -0.169, μ_F = -.260) and effort (μ_M = -1.536, μ_F = -0.875), only the component of value was statistically significant at the Bonferroni corrected alpha level of .008, $t(28)= 3.123$, p = .004 with females gaining in their value of statistics at a statistically greater rate than males. The value component measured students' views regarding the usefulness, relevance, and worth of statistics in their personal and professional life (Schau, 2005). It should also be noted that adequate power was not achieved (d = .8, 1- β = .69, N_{Female} = 16, N_{Male} = 14).

Table 10

Comparison of Mean SATS© Gain Scores by Gender

	t value	*df*	Probability	*M*
Affect	1.146	28	.262	0.429
Cognitive Competence	2.130	28	.042	0.429
Difficulty	1.142	28	.263	0.269
Effort	1.994	28	.056	0.661
Interest	1.625	28	.115	0.516
Value	3.123	28	.004*	0.829

* denotes significant difference at .008

* *M* represents the average male SATS© gain score subtracted from the average female gain score.

Summary

Chapter 4 examined findings for all five research questions. While no statistically significant differences were detected in research question one regarding students' attitudes towards statistics or research question four examining knowledge of statistics by mindset category in the treatment group, statistically significant differences were detected in the remaining questions. Research questions two and three revealed that differences existed between students in the control group and the mindset treatment group regarding students' attitudes toward statistics and knowledge of statistics. A final statistically significant difference was detected in research question five concerning the differences in the change in attitudes toward statistics between males and females in the treatment group. Chapter 5 presents a summary of this research and literature review, as well as findings, conclusions, discussion, and recommendations for practice and future research.

CHAPTER 5

Summary, Conclusions, Discussion, and Recommendations

Chapter 5 provides closure to this study that focused on the effects of mindset, and an intervention of incremental mindset training, on students' attitudes toward statistics and mastery of statistical content in an introductory statistics college course. The chapter opens with a summary of the research followed by conclusions. A discussion of the results, recommendations for practice, and recommendations for future research close the chapter.

Summary

This research examined the effects of mindset, and an intervention of incremental mindset training, on students' attitudes toward statistics and student mastery of statistical content in an introductory statistics course of a small, faith-based, liberal arts college in the Midwest.

Purpose. The purpose of this research was to learn more about the effects of college students' implicit theories of knowledge on their success in an introductory statistics course. Introductory statistics is a class that is required for many majors and the number of students who take statistics continues to grow (Onwuegbuzie & Wilson, 2003). Simultaneous to the growth in statistics courses, research on implicit theories of knowledge has expanded. Unfortunately, only a handful of studies have examined how to create a growth mindset in the college-level mathematics classroom (Kim & Kellert, 2010). This research answers the call from Dweck (2008) to "study ways in which the education environment can teach and support a growth mindset over time" (p. 2). The results of this study add to the research of implicit theories of knowledge in undergraduate statistics courses and support continuous improvement in undergraduate statistics pedagogy. A noteworthy contribution of this research is the positive increases by gender for females in the treatment group regarding students' attitudes toward statistics.

Literature review. A comprehensive literature review revealed relevant research regarding statistics education and cognitive learning theory with a focus on mindset theory. Introductory statistics courses have experienced changes and challenges throughout the past century as the enrollment and diversification of students enrolled in these courses has dramatically increased. One challenge for many students and educators is the anxiety and negative attitudes that students hold towards statistics (Chiesi & Primi, 2010; Evans, 2007; Kesici et al., 2011; Onwuegbuzie & Wilson, 2003; Ruggeri, Dempster, et al., 2008). These challenges, along with an increased number of students with decreased ability, have pushed educators to examine best practices for teaching introductory statistics (Kesici et al., 2011). As a result, numerous instruments have been developed to measure student retention of material, engagement, and attitudes towards statistics. *The Guidelines for Assessment and Instruction in Statistics Education*, published by the American Statistical Association in 2003, is a seminal work that continues to spur the development of statistics education (Aliaga et al., 2005).

Parallel to the increased research in statistics education, cognitive learning theory has also grown and matured. Cognitive learning theory examines the underlying, often unconscious, thought processes of the learner. These mental processes involve and affect a learner's self-efficacy, self-esteem, and implementation of self-regulation (Good et al., 2012; Usher, 2009). The focus of this research is an area of cognitive learning theory called implicit theories of knowledge. Implicit theories of knowledge, also known as mindsets, are metacognitive processes that an individual holds concerning beliefs about their cognitive abilities (Boekaerts et al., 2003; Burns & Isbell, 2007; Mangels et al., 2006).

Individuals tend to hold one of two distinct belief patterns regarding knowledge (Anderson, 1995). Students with an entity mindset view intelligence as fixed while students with incremental mindsets view intelligence as something that can be developed. These mindsets are domain specific and affect a student's motivation, persistence, effort, response to challenge, and goal setting (Anderson, 1995; Dweck, 2008; Dweck & Leggett, 1988; Heyman & Dweck, 1998; Kim & Kellert, 2010; Mangels et al., 2006).

Research on the effects of mindsets has shown that entity mindsets can be detrimental to students' academic achievements; fortunately, cognitive learning theory does not view students' mindsets as unchangeable. Training students to develop an incremental mindset has shown strong potential (Anderson, 1995; Donohoe et al., 2012; Kim & Kellert, 2010). Subsequently, numerous groups have developed mindset training programs which often include information about the plasticity of the brain, the function of neurons and dendrites, the malleability of intelligence, and self-regulation (Cutts, 2008; Donohoe et al., 2012; Good et al., 2003; Mindset Works Inc., 2008). It is against the backdrop provided by the literature review that the importance of the present study can be understood.

Methodology. A quasi-experimental, pretest-posttest design was used in this quantitative research. The population was undergraduate students at a small, faith-based, liberal arts college in the Midwest. The students were predominantly Caucasian and of traditional college age. While the sample was not randomly selected, it was representative of the students who typically enroll in this course.

The population and sample composition varied for different aspects of this research. For research questions one, four, and five which examined students in the mindset treatment, the population consisted of the 52 students in the two fall 2014 sections of introductory statistics. The sample consisted of the 30 students who completed the pre and post assessments for all three instruments. The population for research question two, which examined students' attitudes towards statistics, was the 234 students in the fall 2013 through fall 2014 semesters in which the SATS© instrument was implemented. The sample was the 141 students who completed all aspects of the pretest and posttest assessments. Research question three examined students' mastery of statistical concepts and used a population of 547 students who completed the introductory statistics course between fall 2011 and fall 2014 semesters. The sample was comprised of 411 students who completed the CAOS instruments.

Three instruments assessed each student's attitude towards statistics, mastery of statistical knowledge, and theory of intelligence. The SATS© instrument assessed students' attitudes towards statistics using a 36-item online instrument which captured students' affect, cognitive competence, value, difficulty, interest, and effort towards statistics. Figure 4 includes a sample question representing each component of the SATS©. The 40-item CAOS was also administered online and focused on each student's conceptual understanding of statistics. Students were given online assessments of the SATS© and CAOS instruments outside of class both at the beginning and again at the close of each semester. Students in the treatment group were also given the TMIS instrument online outside of class both prior to and at the close of the semester. The TMIS assessed each student's theory of intelligence regarding mathematics (Dweck, n. d.). Additionally, students in the treatment group received four 15-minute incremental mindset-training sessions throughout the semester. The goal of the sessions was to help students understand how the brain functions biologically with a focus on the malleability of intelligence.

Component	**Sample Question**
Affect	I will like statistics.
Cognitive Competence	*I will have trouble understanding statistics because of how I think.
Value	*Statistics is worthless
Difficulty	Statistics is a subject quickly learned by most people.
Interest	I am interested in understanding statistical information.
Effort	I plan to work hard in my statistics course.

Figure 4. SATS© Component Questions. Each question represents a typical question representing each component of the SATS© instrument.

* The asterisk (*) represents a reversed scored item.

The course instructor for the treatment group was an experienced adjunct instructor with a strong interest in the research. The instructor received an introduction to implicit theories of intelligence and proceeded to read more materials to support the research through a conducive classroom environment.

Findings. Robust statistical analysis procedures were used throughout this research. Despite the limited power to detect differences in questions one, four, and five, valuable information was gained regarding students' attitudes and understandings of statistics in relation to their implicit theory of knowledge and the role of growth mindset treatments.

1. The initial mindset categorization of fixed or growth had no significant effect on the difference in mean SATS© component gains or statistics attitudes. It should be noted that a post hoc power analysis indicated limited power to detect differences (d = .8, 1- β = .30, N_1 = 4, N_2 = 23) (Faul et al., 2009). The mean was calculated as the difference of the average fixed mindset gain score subtracted from the average growth mindset gain score. Non-significant results were found for affect (μ = -0.752, t (25) = -1.439, p = .163), cognitive competence (μ = 0.007, t (25) = 0.022, p = .983), difficulty (μ = -0.184, t (25) = -0.516, p = .610), effort (μ = 0.679, t (25) = 1.310, p = .202), interest (μ = -0.451, t (25) = -0.952, p = .350), and value (μ = 0.093, t (25) = 0.196, p = .846).
2. The treatment group had a significant effect on the component of effort in the posttest SATS© score (μ_{Control} = 5.635, $\mu_{\text{Treatment}}$ = 5.219) assessment when controlling for the pretest SATS© component of effort (μ_{Control} = 5.991,

$\mu_{Treatment}$ = 6.403, $F(1, 138) = 14.778$, $MSE = 10.954$, $p < .001$). The component of effort measured the amount of work the student expended to learn statistics (Schau, 2005). Both the treatment and control group scores dropped from the pretest to the posttest for effort, which is the typical response in an introductory statistics course. While both groups modeled this declining trend in the effort component, the treatment group scores dropped at a statistically significant greater rate than the control group's scores dropped. The remaining attitude components of affect ($F(1, 138) = 3.336$, $MSE = 3.792$, $p = .070$), cognitive competence ($F(1, 138) = .709$, $MSE = 0.431$, $p = .401$), difficulty ($F(1, 138) = 0.085$, $MSE = 0.035$, $p = .771$), interest ($F(1, 138) = 0.007$, $MSE = 0.006$, $p = .932$), and value ($F(1, 138) = 2.145$, $MSE = 1.048$, $p = .145$) showed no significant differences as a result of the treatment group.

3. Students in the control group ($\mu_{Pretest} = 0.487$, $\mu_{Posttest} = 0.598$) improved more than the treatment group ($\mu_{Pretest} = 0.504$, $\mu_{Posttest} = 0.555$) on the posttest CAOS score, their conceptual understanding of statistics, when controlling for the pretest CAOS score ($F(1, 408) = 5.860$, $MSE = .082$, $p = .016$).
4. No difference was found between students categorized with fixed ($\mu = -0.022$) and growth mindsets ($\mu = 0.043$) on the change in statistical knowledge as assessed by the CAOS gain score, $t(25) = -0.889$, $p = .224$. It should be noted that adequate power to detect differences was not achieved in the sample size ($d = .8$, $1- \beta = .30$, $N_1 = 4$, $N_2 = 23$) (Faul et al., 2009).
5. A statistically significant difference was detected for the mean SATS© gain score component of value between genders in the treatment group with

females gaining at a rate greater than males' gain (μ_{Diff} = 0.829, $t(28)$= 3.123, p = .004). The mean difference, μ_{Diff}, was calculated as the average male mindset gain score subtracted from the average female mindset gain score. The remaining attitude components of affect (μ_{Diff} = 0.429, $t(28)$= 1.146, p = .262), cognitive competence (μ_{Diff} = 0.429, $t(28)$= 2.130, p = .042), difficulty (μ_{Diff} = 0.269, $t(28)$= 1.142, p = .263), effort (μ_{Diff} = 0.661, $t(28)$= 1.994, p = .056), and interest (μ_{Diff} = 0.516, $t(28)$= 1.625, p = .115) showed no significant differences between genders. It should be noted that the sample size produced reduced power for this analysis (d = .8, 1- β = .69, N_{Female} = 16, N_{Male} = 14).

Conclusions

Based on this limited sample which research the effects of implicit theories of knowledge, and an intervention of incremental mindset training, in a college introductory statistics course on students' attitudes towards statistics and student mastery of statistical content, the following conclusions emerged.

1. The initial mindset categorization reflects little effect on either students' attitudes towards statistics or their change in statistical knowledge throughout an introductory statistics course.
2. The effect of a mindset treatment on students' attitudes towards statistics and student mastery of statistical content is either non-existent or resulted in a decrease.
3. The effect of mindset treatments is especially beneficial to females since females increased their value of statistics during mindset treatments at a significantly higher rate than males' increase for the SATS© component of value. This is a

significant finding given the historical underrepresentation of women in the field of mathematics (Dweck, 2008; Good et al., 2003). This increase for the component of value compared to males supports the notion that environments that communicate an incremental view of mathematics will increase and improve the achievement of females in mathematics and science (Good et al., 2012).

Discussion

The discussion portion of this paper attempts to discuss and make conclusions based on the findings in this study. One purpose of this study was to determine if there were differences between students categorized with fixed and growth mindsets. An additional objective of the research was to determine the efficacy of training to develop incremental mindsets. The section opens with unexpected nature of the results and external factors affecting the treatment semester, followed by an examination of the distribution of initial mindsets towards mathematics. Factors affecting attitudes and achievement are covered and the section closes with considerations regarding the conceptual curriculum implemented in the course and the role of the instructor in the treatment group.

Unexpected results. The initial mindset categorization had little effect on students' attitudes towards statistics or their change in statistical knowledge throughout an introductory statistics course. This conclusion does not coincide with information in the literature review which suggests that students' mindsets affect motivation (Ames, 1992; Elliott & Dweck, 1988; Zimmerman, 2000), effort (Blackwell et al., 2007), and self-efficacy (Anderson, 1995; Dweck & Leggett, 1988).

Additional unexpected results were the lack of effect or negative effect of a mindset treatment on students' attitudes towards statistics and student mastery of statistical content. The decrease in the value of effort for students in the treatment group does not coincide with Dweck and Leggett's (1988) research which found that an individual's view toward effort was positively associated with an incremental mindset. The statistically significant decrease among students' mastery of statistical concepts in the treatment group also does not coincide with Blackwell and colleagues' (2007) landmark research demonstrating the positive achievement growth among students who received incremental mindset treatments. One possible explanation is the amount and frequency of the incremental mindset treatments was not adequate to produce the expected effects.

External factors. It was discovered during a response rate check during the posttest that the student invitation to complete the SATS© and CAOS had not been sent. The administrative assistant in charge of communication had only requested the TMIS posttest. Thus, students were invited to complete the posttest assessments on the first day of exams. Students were then given four days to complete the posttest SATS© and CAOS, instead of the originally planned seven days similar to the control group. The response rate for the pretest assessments was 96.1% while the posttest rate was only 55.8%. The researcher believes that the invitation oversight negatively affected not only the response rate of students, but also the quality of the results of the SATS© and CAOS as the posttest window was more brief and coincided with an inopportune time to obtain students' responses.

Another consideration regarding the findings in this study is the numerous changes that took place during the treatment semester. It is unknown the effect to which the change from a three-credit to a four-credit course had on students' attitudes and achievement. With the additional credit, students completed a research project and learned to use a statistical software program that uses the *R* language. These new tasks may have affected students' attitudes negatively.

The instructor in the treatment group also represented a change from the instructors in the control group. Previous semesters were taught by tenure-track professors and the treatment group was taught by an adjunct instructor. It is unknown how these changes may have affected the results, although the literature review does support the importance of the educator in fostering students' mindsets (Dweck, 2006; Good et al., 2012; Kamins & Dweck, 1999; Rattan et al., 2012). Another possible consideration is the character of the instruction since the CAOS focuses on conceptual understanding. Differences between instructors and each instructor's conceptual understanding of statistics may have played a role in the results.

Distribution of initial mindset. An unexpected result in this research was the high level of students who identified with incremental mindsets. Of the 50 students who completed the pretest TMIS, only five (10% of the population) identified with entity mindsets. This is substantially lower than Dweck's (2006) findings that approximately 40% of individuals identify with incremental mindsets, 40% entity mindset, and the remaining 20% of individuals being too ambiguous to classify. Of the five students who identified with fixed mindsets, four completed the posttests. This left only four students upon which to draw conclusions about students with entity mindsets, thus severely limiting the power and generalizability of the results.

The high percentage of students who identified with an incremental mindset ($\hat{p}$ = .78) raises interesting questions: (1) Is it typical for students who pursue higher education to tend to hold incremental mindsets? (2) Do students with entity mindsets pursue higher education at lower rates and, thus, are underrepresented in the sample? (3) Is this finding a peculiarity of the specific college or of a specific demographic of the institution such as its faith-based nature or geographic location? It is unclear why students with incremental mindsets were overrepresented in this sample. No research was uncovered in the literature review to support the first or second hypotheses that students with incremental mindsets pursue higher education at greater rates. The results may confirm Kristjansson's (2008) criticism that the theories of intelligence instruments are too dichotomous for the reality of individuals who rarely fit neatly into two categories. More research is necessary to discern if these results are due to random chance or a bias present in the current sample.

Factors affecting attitudes. While the response rate was lower than expected and did not produce significant results, the students with growth mindsets did show small, but insignificant increases in their attitudes towards statistics. This is an important finding as it may add to Evans (2007) research which reported no methods for instructors to help improve students' attitudes towards statistics. This may also suggest that an increased emphasis on attitude, alongside mindset, is necessary in the treatment to see improvements in students' attitudes towards statistics. More research needs to be done to explore this finding in greater depth.

The literature review supported the hypothesis that attitudes towards mathematics and achievement were connected (Aiken, 1970; Chiesi & Primi, 2010; Evans, 2007; Nolan et al., 2012). Additional research regarding the connection between mathematics achievement and students' implicit theories of knowledge was also uncovered (Dweck, 2008). Based on these connections, it was hypothesized that the mindset treatment would improve students' attitudes towards statistics. Specific components expected to show improvement were effort and cognitive competence (Blackwell et al., 2007; Dweck, 1999, 2010; Dweck & Leggett, 1988); however, no changes were present with the exception of the component effort which showed a decrease. Continued research to increase the sample size is necessary to learn more about these unexpected results.

Changes in effort. Multiple hypotheses exist regarding the change in the effort component for the SATS©. One hypothesis is that the change is a byproduct of the different classes and instructors that students experienced. Instructors vary in their difficulty, classroom environment, and instructional approach. Furthermore, students in the treatment sections experienced the addition of a research project and statistical software program that may have affected how students responded to the component of effort.

Another possibility in regard to the statistically significantly greater decrease in effort among the treatment group is the possibility that the treatment caused an inverse response. A focus throughout the treatments was giving students positive strategies for responding to their newly gained knowledge. Effort was highlighted in the treatments along with strategies to improve the quality of studying. It is possible that the emphasis on effort failed, producing greater decreases in the effort component.

Adding to the idea of a possible inverse effect of the treatment for the effort component in the treatment groups may be the role of contingent self-worth. In three studies conducted at the University of Michigan at Ann Arbor, Niiya, Brook, and Crocker (2010) found differences in the behavior of students holding incremental theories based on their contingent self-worth. Specifically, they found that "having an incremental theory can promote self-handicapping on difficult tasks when combined with contingent self-worth" (p. 293). This self-handicapping behavior allows students to attribute failure to effort, or weak study strategies, rather than ability. For students with incremental mindsets, the advantage of these attributions is that they are controllable and allow the student to continue to believe that they could have success in the future if they exerted increased effort. This concurs with Harari and Covington's (1981) research which found that students will use effort attributions only if they believe that their intelligence can be improved. Following this line of thought, the decrease observed in the attitude component of effort for the treatment group could be an example of an attribution. This is plausible given the predominance of incremental mindsets held by the treatment group.

Differences by gender. An encouraging finding in the treatment group showed a statistically significant improvement for the 16 females compared to the 14 males on the SATS© for the value component. This is an important result as it may help combat the underrepresentation of females in science, technology, engineering, and mathematics (STEM) fields. If incremental mindset training helps females value mathematics, it may also improve their performance to help diminish a persistent stereotype in the mathematics community that males are more capable of mathematical thinking and quantitative reasoning than females (Dweck, 2008; Good et al., 2003; Good et al., 2012).

Related positive differences, though non-significant, were also noted for the components of cognitive competence and effort.

Factors affecting concept mastery. Similar to students' attitudes towards statistics, it was expected that students in the treatment would increase their mastery of statistical concepts (Blackwell et al., 2007). In reality, students who received the treatment gained at a statistically significant decreased rate. As was seen in Figure 3, the gain in statistical knowledge as measured by the CAOS varies by semester. While the gain for the treatment semester (fall 2014) was the lowest for the semesters in which the CAOS was administered, it should be noted that the students' pretest CAOS scores were among the highest present in the available data. It is possible that an inverse relationship exists between students' pretest CAOS scores and their gain scores. This may also indicate the possibility of a ceiling effect for posttest CAOS scores. An additional consideration regarding mastery is the effect, as Donohoe (2012) questioned the efficacy of brief interventions doubt regarding the ability to show large differences with brief interventions may also have played a role in the research.

The greater achievement gains for the control group, as measured by the CAOS assessment, support recent findings at the University College London and Temple University which found no "connection between students' theories of intelligence and their grades" (Glenn, 2010, p. 7). One hypothesis made regarding the unexpected results at Temple University was that it was a less-selective institution than the universities where previous incremental mindset research were conducted. Thus, improvements in students' implicit theories of knowledge may have been swamped by students' "baseline knowledge about how to navigate through college life" (Glenn, 2010, p. 7). The findings of this study accentuate the importance of continued research on the role of students' mindsets regarding achievement in a wide range of settings.

Curricular factors. Another consideration regarding the present study was the reform curriculum that was implemented throughout the study. Tintle and colleagues (2014) have demonstrated significant achievement improvements in introductory statistics courses when compared to courses that implement traditional curricula. It is plausible that the conceptual approach to the class improves students' achievements and thus makes the mindset treatments less effective. Furthermore, gains could have been present in a traditional, introductory statistics course that did not have a conceptual approach.

Instructor impact. A final consideration regarding this research was the role of the instructor in the treatment group. There is growing evidence that teachers' mindsets affect their pedagogy and interactions with students (Dweck, 2006; Good et al., 2012; Kamins & Dweck, 1999; Rattan et al., 2012). The instructor for the control group was an adjunct instructor with a highly successful high school teaching career spanning more than forty years. He was debriefed on mindsets and the importance of fostering an incremental mindset. The instructor was excited about the opportunity to participate in this mindset research and, of his own volition, read additional materials to gain a better understanding and shared research articles with the researcher. The instructor commented numerous times throughout the treatment semester how valuable the treatments were, especially for students in his classes who were pre-service teachers. One indicator of the instructor's support of the mindset treatment was his request that the treatment be repeated in the following semester. As a result of the instructor's successful teaching career, interest in mindset theory, and support of the research, the instructor was not considered to be an intervening variable.

Recommendations

Recommendations for practice. The following recommendations regarding educational practice are a result of the findings in this research.

1. Educators should continue to foster growth mindsets in their classroom. An analysis of the pretest and posttest TMIS scores revealed that four of the five students who experienced the largest increase in their TMIS score were the four students classified with fixed mindsets. The average growth for the treatment group on the TMIS was 0.092, whereas the four students with fixed mindsets increased an average of 1.761 in their pretest to posttest TMIS assessment. Additionally, the two students with ambiguous mindsets improved an average of 0.815 on their TMIS gain score.
2. Mindset treatments should include information regarding the physiology of the brain, explanations of the two mindsets including role models portraying them, and the role of effort. This recommendation is based on an additional question in the TMIS posttest asking students in the treatment to rank each of the mindset treatments from (1) most effective to (4) least effective. Findings are displayed in Table 11. The first ($\mu 1$ = 2.0) and the last treatments ($\mu 4$ = 2.4) were considered most effective, receiving the lowest average and the highest percent of number 1 rankings (Treatment 1 = 41.4%, Treatment 4 = 31.0%).

Table 11

Mindset Treatment Rankings

Session	Topics	*M*	Percentage #1
1	Fixed and Growth Mindsets Brain Physiology	2.0	41.4%
2	Response to Feedback Helplessness and Mastery Responses	2.8	13.8%
3	Performance Goals and Learning Goals Set Course Goals	2.8	13.8%
4	Examples of Fixed and Growth Mindsets in Role Models The Role of Effort	2.4	31.0%

* Percentage refers to the percent of #1 rankings the treatment received.

Recommendations for research. The following recommendations are made regarding further research into the role of mindsets and incremental mindset training on students' achievements and attitudes.

1. Since the current study lacked adequate power to detect differences in the treatment group, a replication of the study in the same school would be useful to increase the sample size. The initial results suggest that the gain of statistical knowledge for students with growth mindsets is greater. Replication would increase the power to detect useful information regarding

the differences between students with fixed and growth mindset attitudes towards statistics and mastery of statistical concepts. Additional research will also add valuable information regarding the breakdown of individuals by mindset in undergraduate settings, specifically at this institution.

2. Given the unexpected findings in both the present study and those conducted at the University of Michigan at Ann Arbor, more research on the role of mindsets and incremental mindset training should be conducted in various settings at the college level to improve the generalizability of results (Niiya et al., 2010).
3. Given the limitations present in the current research introduced by the change from a three-credit to four-credit course, the pretest and posttest CAOS and SATS© assessments should continue to be implemented in introductory statistics courses. Performing this research in future semesters with other instructors will also address any differences that may be tied to the instructor, not the treatment.
4. Given the inconvenient timing of the posttest implementation, students should be invited to the complete the posttest portion of the assessments in the week prior to exams. This change will avoid assessing students during exam time which is known to produce stress (Hughes, 2005; Rayle & Chung, 2007). Possible benefits of administering the assessments prior to exams are an increased response rate and increased quality of responses.
5. Further research into the effect that gender has on students' attitudes towards statistics should explore why males and females differ in their responses from

pretest to posttest. Research should replicate the current quantitative study to increase the sample size, but also add an aspect of qualitative research to understand why males and females respond in different ways. Research should be done on the role that instructor gender has on students' attitudes towards statistics. The specific focus should be how male and female students' attitudes towards statistics varies according to the gender of the instructor.

6. Research should expand to other mathematics courses including remedial and advanced classes. This generalization will give educators and researchers a deeper understanding of the role that mindset and mindset treatments have on students' attitudes towards mathematics and achievement in additional courses.

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Appendix A

Survey of Attitudes Toward Statistics Pre-Test

Survey of Attitudes Toward Statistics - Pre

DIRECTIONS: The statements below are designed to identify your attitudes about statistics. Each item has 7 possible responses. The responses range from 1 (strongly disagree) through 4 (neither disagree nor agree) to 7 (strongly agree). If you have no opinion, choose response 4. Please read each statement. Mark the one response that most clearly represents your degree of agreement or disagreement with that statement. Try not to think too deeply about each response. Record your answer and move quickly to the next item. Please respond to all of the statements.

	Strongly disagree			Neither disagree or agree			Strongly agree
1. I plan to complete all of my statistics assignments	1	2	3	4	5	6	7
2. I plan to work hard in my statistics course.	1	2	3	4	5	6	7
3. I will like statistics.	1	2	3	4	5	6	7
4. I will feel insecure when I have to do statistics problems.	1	2	3	4	5	6	7
5. I will have trouble understanding statistics because of how I think.	1	2	3	4	5	6	7
6. Statistics formulas are easy to understand.	1	2	3	4	5	6	7
7. Statistics is worthless.	1	2	3	4	5	6	7
8. Statistics is a complicated subject.	1	2	3	4	5	6	7
9. Statistics should be a required part of my professional training.	1	2	3	4	5	6	7
10. Statistical skills will make me more employable.	1	2	3	4	5	6	7
11. I will have no idea of what's going on in this statistics course.	1	2	3	4	5	6	7
12. I am interested in being able to communicate statistical information to others.	1	2	3	4	5	6	7

	Strongly disagree			Neither disagree or agree			Strongly agree
13. Statistics is not useful to the typical professional.	1	2	3	4	5	6	7
14. I plan to study hard for every statistics test.	1	2	3	4	5	6	7
15. I will get frustrated going over statistics tests in class.	1	2	3	4	5	6	7
16. Statistical thinking is not applicable in my life outside my job.	1	2	3	4	5	6	7
17. I use statistics in my everyday life.	1	2	3	4	5	6	7
18. I will be under stress during statistics class.	1	2	3	4	5	6	7
19. I will enjoy taking statistics courses.	1	2	3	4	5	6	7
20. I am interested in using statistics.	1	2	3	4	5	6	7
21. Statistics conclusions are rarely presented in everyday life.	1	2	3	4	5	6	7
22. Statistics is a subject quickly learned by most people.	1	2	3	4	5	6	7
23. I am interested in understanding statistical information.	1	2	3	4	5	6	7
24. Learning statistics requires a great deal of discipline.	1	2	3	4	5	6	7
25. I will have no application for statistics in my profession.	1	2	3	4	5	6	7
26. I will make a lot of math errors in statistics.	1	2	3	4	5	6	7
27. I plan to attend every statistics class session.	1	2	3	4	5	6	7
28. I am scared by statistics.	1	2	3	4	5	6	7
29. I am interested in learning statistics.	1	2	3	4	5	6	7
30. Statistics involves massive computations.	1	2	3	4	5	6	7

	Strongly disagree			Neither disagree or agree			Strongly agree
31. I can learn statistics.	1	2	3	4	5	6	7
32. I will understand statistics equations.	1	2	3	4	5	6	7
33. Statistics is irrelevant in my life.	1	2	3	4	5	6	7
34. Statistics is highly technical.	1	2	3	4	5	6	7
35. I will find it difficult to understand statistical concepts.	1	2	3	4	5	6	7
36. Most people have to learn a new way of thinking to do statistics.							

Please notice that the labels for each scale on the rest of this page change from item to item.

	Very poorly						Very well
How well did you do in mathematics courses you have taken in the past?	1	2	3	4	5	6	7

	Very poor						Very good
How good at mathematics are you?	1	2	3	4	5	6	7

	Not at all						Great deal
In the field in which you hope to be employed when you finish school, how much will you use statistics?	1	2	3	4	5	6	7

	Not at all confident						Very confident
How confident are you that you can master introductory statistics material?	1	2	3	4	5	6	7

	Yes	No	Don't know
Are you required to take this statistics course (or one like it) to complete your degree program?	1	2	3

	Not at all likely						Very likely
If the choice had been yours, how likely is it that you would have chosen to take any course in statistics?	1	2	3	4	5	6	7

DIRECTIONS: For each of the following statements mark the <u>one</u> best response. Notice that the response scale changes on each item.

What is your major? If you have a double major, pick the one that bests represents your interests.

1. Arts/Humanities	6. Education	11. Soc./Social Work
2. Biology	7. Engineering	12. Statistics
3. Business	8. Mathematics	13. Other
4. Chemistry	9. Medicine/Pre-Medicine	
5. Economics	10. Psychology	

Current grade point average (please estimate if you don't know; give only one single numeric response: e.g., 3.52). If you do not yet have a grade point average, please enter 99: ______________

For each of the following three items, give one single numeric response (e.g., 26). Please estimate if you don’t know exactly.

Number of credit hours earned toward the degree you are currently seeking (don’t count this semester): ______________

Number of high school mathematics and/or statistics courses completed: ______________

Number of college mathematics and/or statistics courses completed (don’t count this semester): ______________

Degree you are currently seeking:

1. Associate	5. Certification
2. Bachelors	6. Post-bachelor's Licensure
3. Masters	7. Specialist
4. Doctorate	8. Other

What grade do you expect to receive in this course?

1. A +	5. B	9. C-	13. F
2. A	6. B-	10. D+	
3. A-	7. C+	11. D	
4. B+	8. C	12. D-	

In order to describe the characteristics of your class as a whole, we need your responses to the following items.

Your sex: 1. Male 2. Female

Your citizenship: 1. US citizen 2. Foreign student 3. Other

Your age (in years): _____

THANKS FOR YOUR HELP!

Appendix B

Scoring the SATS-36©

Scoring the SATS-36©

Component (subscale) scores on the SATS-36© are formed by

1. Reversing the responses to the negatively worded items indicated with an asterisk* (1 becomes 7, 2 becomes 6, etc.),
2. Summing the item responses within each component, and
3. Dividing by the number of items within each component.

The possible range of scores for each component is between 1 and 7. Using the 7-point response scale, higher scores then correspond with more positive attitudes.

The SATS-36© contains 36 items. These items include the same ones found in the SATS-28© as well as eight more designed to assess two additional components: Interest and Effort. The SATS-36© also contains three single global attitude items in both the pretest and posttest versions as well as a global Effort item contained in the posttest version only. Additional items ask for relevant demographic and academic background information.

Six Attitude Components:

The following lists the individual 36 items (from the pretest version) grouped into the six attitude components. Item numbers are the same in the pre and the post versions.

Affect –Students' feelings concerning statistics

3. I will like statistics.
4.* I will feel insecure when I have to do statistics problems.
15.* I will get frustrated going over statistics tests in class.
18.* I will be under stress during statistics class.

19. I will enjoy taking statistics courses.
28.* I am scared by statistics.

Cognitive Competence – students' attitudes about their intellectual knowledge and skills when applied to statistics

5.* I will have trouble understanding statistics because of how I think.
11.* I will have no idea of what's going on in this statistics course.
26.* I will make a lot of math errors in statistics.
31. I can learn statistics.
32. I will understand statistics equations.
35.* I will find it difficult to understand statistical concepts.

Value – students' attitudes about the usefulness, relevance, and worth of statistics in personal and professional life

7.* Statistics is worthless.
9. Statistics should be a required part of my professional training.
10. Statistical skills will make me more employable.
13.* Statistics is not useful to the typical professional.
16.* Statistical thinking is not applicable in my life outside my job.
17. I use statistics in my everyday life.
21.* Statistics conclusions are rarely presented in everyday life.
25.* I will have no application for statistics in my profession.
33.* Statistics is irrelevant in my life.

Difficulty – students' attitudes about the difficulty of statistics as a subject

6. Statistics formulas are easy to understand.
8.* Statistics is a complicated subject.

22. Statistics is a subject quickly learned by most people.

24.* Learning statistics requires a great deal of discipline.

30.* Statistics involves massive computations.

34.* Statistics is highly technical.

36.* Most people have to learn a new way of thinking to do statistics.

Interest – students' level of individual interest in statistics

12. I am interested in being able to communicate statistical information to others.

20. I am interested in using statistics.

23. I am interested in understanding statistical information.

29. I am interested in learning statistics.

Effort – amount of work the student expends to learn statistics

1. I plan to complete all of my statistics assignments.

2. I plan to work hard in my statistics course.

14. I plan to study hard for every statistics test.

27. I plan to attend every statistics class session.

Appendix C

Theories of Math Intelligence Scale –Self Form

Theories of Math Intelligence Scale-Self Form

Please show how much you agree or disagree with each statement by writing the number that corresponds to your opinion in the space next to each statement.

There are no right or wrong answers. We are interested in your ideas.

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

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

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

___3. To be honest, you can't really change how intelligent you are in math.

___4. You can learn new things, but you can't really change your basic math intelligence.

Appendix D

Scoring the TMIS

Scoring the Theories of Math Intelligence Scale-Self Form

To calculate an individual's theory of math intelligence, find the average of the four responses above. (Add all responses and divide by four.) The resulting average is then categorized as entity, incremental, or ambiguous.

TMIS Average	**Mindset Category**
1 – 2.9	Entity
3-4	Ambiguous
4.1 – 6	Incremental

Appendix E

Treatment Protocol

Session 1: An introduction to mindsets and the physiology of the brain

- Introductions:
    - Describe the study
    - Introduce a fixed and a growth mindset
- The challenge of Statistics
    - First time experience for many students
    - Similar to learning a new language
    - Expect to make mistakes
    - How will you respond to mistakes?
- Reading activity: The class will be divided into two groups with each group reading one of the following articles:
    - You Can Grow Your Intelligence by Blackwell (2002)
    - Mindset and Your Brain by Cutts (2008) (See Appendix F)
- **Consolidation:** Whole class discussion with guiding questions adapted from Dooms (2013)
    - What does new research say about the brain?
    - When you learn new things, what happens to your brain?
    - What differences were noticed in animals' brains in your articles?
    - Give a specific example from the article or your own life where your brain has grown.
    - What can you do to help your brain grow?
    - How will you help yourself learn statistics?

Session 2: Response to Feedback /Helpless and Mastery Response

(Takes place after the first test)

- Introduce with Card Sort Activity (Dooms, 2013) (See Appendix G)
- Describe Helpless and Mastery Responses
- Thought Questions adapted from Cutts (2008) (Led as a group):
    - Do you switch off and not pay attention to potentially useful information?
    - Do you blame yourself (i.e. your ability), when you do not get high marks?
    - Do you focus on how you are feeling when you get results back, rather than what you can learn?
    - You can change and research shows that doing so will change your brain.
- Written reflection on the first statistics test:
    - What surprised you on the test?
    - What were you comfortable with?
    - What behaviors <u>will not</u> help you on the next test?
    - What behaviors <u>will</u> help you on the next test?
- **Consolidation:** How can you adopt more of a mastery response when you receive feedback? (Led as a group) Cutts (2008)
    - Think about what you can learn rather than how you feel.
    - Examine your areas of weaknesses and make a strategy for working on them.
    - Ask for advice from people who did well in the areas where you did not.

    - Focus on how to improve from the feedback - research shows that this can actually change your brain.
    - Keep looking for new ways to learn if one way is not working. E.g. The professor's explanation does not make sense, where else can I go?
    - Remember that each time you study or find new ways to do things your brain grows new connections and strengthens existing brain pathways.
- Close with YouTube: I Can't Yet
    - https://www.youtube.com/watch?v=ZyAde4nIIm8
    - 1 minute

Session 3: Performance Goals and Learning Goals/Course Goals

- Introduction Youtube video: Growth vs. Fixed Mindset
    - https://www.youtube.com/watch?v=brpkjT9m2Oo
    - 1 minute
- Describe Performance and Mastery goals
- **Consolidation**: Written reflection (Cutts, 2008)
    - Why did you enroll in this class?
    - What are your goals for the course?
    - When you hit an obstacle, this is a sign that you have something to learn. How can you respond positively?
    - If you receive feedback that you have the correct answer, how can you make sure that you also understand *why* or *how* it is correct?
    - What is currently your weakest topic or skill in statistics? How can you learn more about this?

Session 4: Examples of Mindsets in Role Models/the Role of Effort

- Video: Famous Failures

  https://www.youtube.com/watch?v=zLYECIjmnQs&safe=active

- Presentation: Examples of individuals with fixed and growth mindsets Maryland Educators of Gifted Students (2011)
  - Winston Churchill
  - Beethoven
  - Tolstoy
  - Michael Jordan
  - Walt Disney
  - Alfred Binet and the IQ test
  - John MacEnroe
- Discussion of the role of effort
  - Why effort threatens individuals with fixed mindsets
  - The 10,000 Hour rule from Outliers by Gladwell (2008)
  - Examples of the 10,000 hour rule: Bill Gates, Bill Joy, Berlin's Academy of music, Mozart, The Beatles
- **Consolidation**: Written Reflection
  - What are you good at? How did you become good?
  - Remember the goals for the course that you wrote earlier, how can effort help you reach your goals?
- Close with motivational Youtube video from Mindset Max
  - https://www.youtube.com/watch?v=p5ac3k4wqW4

- 2.5 minutes, skip commercial at end

Appendix F

Mindset Article

Mindset and the Brain (Cutts, 2008)

It was once believed that by a certain age, sometime during childhood, the brain stops making new cells and connections. People thought that aspects such as personality and intelligence were fixed and that there wasn't much anyone could do to change that.

There is now, however, an overwhelming body of research showing that this is not true and that people grow new brain connections throughout their lives. The research suggests that people can change the structure and function of their brain through the experiences they have. The results come from a wide range of observations and scientific findings:

1. People who have damaged areas of their brain, and have lost certain functions such as speech, can recover the lost function (i.e. speech) by using other areas of their brain. The brain rewires. This comes from various different strands of research such as stroke victims and people who have lost limbs. It takes concerted effort, but it is possible.
2. Those who put a large amount of effort into a particular activity can actually change the structure of their brains - they have bigger areas depending on what it is that they are practicing. For example, it has been shown that people who play music extensively have a bigger auditory cortex (the area responsible for processing sound) and taxi drivers have a bigger hippocampus (the area responsible for spatial memory).
3. Research shows that practice strengthens the connections in the brain; "neurons that fire together wire together". The more an activity is practiced the stronger the connections the neurons make and the deeper the learning.
4. Adopting a growth mindset changes the way people use their brain. A neuroscience study with university students showed that those adopting a growth mindset paid attention to feedback and this used different areas of their brains. The result of the study showed that they did better on the next test.
5. Many studies have shown that mindset can be changed and is a matter of individual choice: people can change their mindset towards an area simply by being aware of the research and acting on the findings. Knowing about the brain and its capacity for change supports this shift in attitude.

Examples of Mindset and brain

1. One of the world's most famous neuroscientists, Paul Bach-Y-Rita, moved into this profession as a result of his father's having a stroke and losing all ability to speak and walk. The rehabilitation experts said there was nothing they could do for him and sent him home. Bach-Y-Rita was determined that his father would learn to walk and talk again and so he spent hours teaching his father to relearn these skills, by breaking each goal down into smaller steps. For example, when teaching him to crawl he looked at the steps babies go through and applied them to his father. The result was that his father learned to walk and talk again and resumed a teaching position back at his university. Bach -Y-Rita's father died some years later climbing a mountain. When an autopsy was performed, the areas damaged by the stroke were found to be still

damaged. The assumption Bach-Y-Rita made was that other areas of his father's brain must have developed the connections necessary to control walking and talking.

2. Rats were placed in one of two environments: a boring one and an exciting one. Researchers showed that those in the more stimulating environment had heavier brains - the environment caused this. They also found that the rats in the rich environment were better at learning to get around a water maze.

3. The brain is made up of billions of cells called neurons. The brain communicates messages via these neurons. Donald Hebb the famous Canadian Psychologist, showed, as far back as 1949, that neurons active at the same time increase the strength of their connection. He coined the phrase "Cells that fire together, wire together" What this means is that when an axon of one cell repeatedly stimulates another cell, over time the efficacy with which the former stimulates the latter is increased via some essential metabolic change on the part of one or both of the cells involved. This idea has since been supported by a wealth of empirical evidence. To summarize, synapses (unions between neurons) get solidified the more often the respective neurons "talk" to each other.

4. A study at New York University showed that students who adopted a growth mindset showed different brain responses to feedback compared to fixed mindset. All students were hooked up to an EEG machine - to measure brain activity. The researchers measured their mindset. The students were then given a set of difficult multiple-choice questions to answer. Each time they got a wrong answer (or right answer) they were given the correct answer. When students found out whether they got the answer correct the attentional areas of the brain were active, in both mindset groups. However, when students were given the correct answers after getting a question wrong only the growth mindsetters paid attention. The fixed mindsetters had increased activity in the emotional areas of the brain - they were more concerned with how they felt after failure. After a surprise retest later, the growth mindsetters performed better. It is interesting to note that students in this study began with the same grade point average, only differing in which mindset they endorsed: either fixed or growth.

5. Research shows that when people learn about the brain and its huge potential for growth throughout life, this can change their mindset, which consequently influences how well they do.

Appendix G

Mindset Card Sort Activity

Fixed Mindset and Growth Mindset Card Sort

Courtesy of (Dooms (2013))

http://teacherleaders.wordpress.com/2013/07/19/math-mindset-and-attribution-retraining/

Cut the following bullet points into strips. Mix them up for students to sort into two categories.

Fixed Mindset

- It is not possible to change your intelligence.
- Mistakes are setbacks.
- I don’t like to take risks if there is a possibility for failure.
- It’s not possible to grow your intelligence.
- If it doesn’t come easily, it means I can’t be good at it.
- Challenges can feel frustrating.
- Looking smart is important.
- A student does not participate for fear of being wrong.
- When a student is unsuccessful on a task, he may feel insecure, study less next time, or even consider cheating.

Growth Mindset

- It is possible to change your intelligence.

- I enjoy taking a risk even if it means I may make a mistake.

- Challenges feel like an opportunity to learn.

- I am interested in learning.

- I turn obstacles into opportunities.

- Students believe they will learn from their mistakes.

- When a student is unsuccessful on a task, he will feel motivates to study more and use different learning strategies to persevere.

- Effort enables me to become successful.

- I'm welcome constructive feedback.

Fixed Mindset

Growth

Mindset

Appendix H

E-mail Invitation

August 28, 2014

I hope that your semester is off to a good start! The purpose of my email is an invitation to participate in research that can help improve your attitude, mindset, and achievement in statistics. This research will also help improve future students' experiences in statistics classes. I am inviting you to be in this study because you are a student in STAT 131.

If you agree to participate, you will take part in the growth mindset training that will occur during class and also complete two pre-test and post-test assessments. Both assessments begin with an initial opt-out screen if you choose not to participate. You are also free to skip any questions with which you are not comfortable. The link and a brief description follows for each assessment:

<Link to SATS/TMIS>

- The first is a nationally standardized assessment of attitudes towards statistics which includes four questions pertaining to your mindset toward mathematics. This will take approximately 15 minutes.

<Link to CAOS>

- The second is a nationally standardized statistics test to gauge your knowledge of statistics prior to and after the course. Please put forth your best effort to ensure accurate information. The test consists of approximately 40 questions and takes most students approximately 20-40 minutes.

This research is a part of my doctoral studies at the University of South Dakota. I will keep the information you provide anonymous; however, federal regulatory agencies and the University of South Dakota Institutional Review Board (a committee that reviews and approves research studies) may inspect and copy records pertaining to this research.

Your responses will be anonymous to ensure that they cannot be linked to you.

There are no known risks from being in this study. All survey responses will be treated confidentially and stored on a secure electronic file that is password protected. No hardcopy of this study's data will be maintained; however, given that the surveys can be completed from any computer (e.g., personal, work, school), I am unable to guarantee the security of the computer on which you choose to enter your responses. As a participant in our study, I want you to be aware that certain "key logging" software programs exist that can be used to track or capture data that you enter and/or websites that you visit.

Your participation in this research study is completely voluntary. If you decide not to be in this study, or if you stop participating at any time, you will not be penalized or lose any benefits for which you are otherwise entitled.

If you have any questions, concerns or complaints now or later, you may contact me at the number below. If you have any questions about your rights as a human subject, complaints, concerns, or wish to talk to someone who is independent of the research, contact the Office for Human Subjects Protections at 605-677-6184. Thank you for your time.

Professor Valorie Zonnefeld

CL1504

712-722-6362

valorie.zonnefeld@dordt.edu

Appendix I

Area Leader Permission

From: Gary De Young [mailto:tekel.enterprises@gmail.com]

Sent: Monday, March 10, 2014 8:19 AM

To: Valorie Zonnefeld

Subject: Re: Permission Requested

I don't see a problem with this.

Gary

On Mar 10, 2014 7:01 AM, "Valorie Zonnefeld" <Valorie.Zonnefeld@dordt.edu> wrote:

Dr. De Young,

I am writing to request permission to conduct research in the fall 2014 sections of introductory statistics. The treatment will consist of four 10-15 minute training sessions in incremental mindset theory. The students in the class already take the Student Attitudes Towards Statistics© (SATS-36) instrument and the Comprehensive Assessment of Outcomes in a First Statistics course (CAOS) assessment for other research. For the purpose of this study, they will also take the four-item Theories of Mathematical Intelligence Scale (TMIS) assessment. I have already received verbal permission from Dr. Nathan Tintle.

I look forward to your response,

Val

Appendix J

Permission Statistics Department

From: nathan.tintle@gmail.com [mailto:nathan.tintle@gmail.com] **On Behalf Of** Nathan Tintle

Sent: Monday, March 10, 2014 10:01 PM

To: Valorie Zonnefeld

Subject: Re: Permission Requested

Val-

You have permission for both of these requests.

On Mon, Mar 10, 2014 at 7:43 PM, Valorie Zonnefeld <Valorie.Zonnefeld@dordt.edu> wrote:

Dr. Tintle,

I am writing to formally request permission to use preexisting data from introductory statistics classes for my dissertation research. The specific data involves the CAOS and SATS© pretest and posttest results for students in the fall 2011 through Spring 2014 semesters.

Additionally, I am writing to you as the head of the Statistics department to request permission to perform four 15-minute incremental mindset training sessions throughout the fall 2014 semester in each section of STAT 131.

Thank you for your consideration,

Val

Appendix K

CAOS Opt-Out Screen

CAOS Opt-out Prompts

Participation on this survey is voluntary. The survey consists of approximately 30 multiple choice questions about statistical concepts. You should try your best. Even though it is a posttest there may be things that you are unsure about---just try your best. Your instructor will be provided a list of names of students who've taken the posttest. Your name will never be associated with your answers and your instructor will not see any of the results until after course grades have been submitted. After a few brief demographic questions (below), and an option to opt-out of taking the posttest click next to take test. If you decide to participate, the test will take approximately 30 minutes. If you decide not participate, please indicate that below and then press the Submit button.

---

7. You can stop taking this survey at any time. Press the Submit button when you have finished. Note: If you decline to participate, your name will still be sent to the instructor for credit.

Appendix L

SATS© Opt-Out Screen

SATS©/TMIS Opt-out Prompts

Participation on this survey is voluntary. The survey consists of approximately 45 multiple choice questions about your attitudes towards statistics. Your instructor will be provided a list of names of students who've taken the survey. Your name will never be associated with your answers and your instructor will not see any of the results until after course grades have been submitted. After a few brief demographic questions (below), and an option to opt-out of taking the survey, click next to take survey. If you decide to participate, the survey will take approximately 15 minutes. If you decide not participate, please indicate that below and then press the Submit button.

---

6. You can stop taking this survey at any time. Press the Submit button when you have finished. Note: If you decline to participate, your name will still be sent to the instructor for credit.

Appendix M

CAOS Permission

From: Robert delMas [mailto:delma001@umn.edu]

Sent: Thursday, March 06, 2014 7:51 PM

To: Valorie Zonnefeld

Subject: Re: CAOS permission

We do prefer to not have the CAOS test items published. Any academic who wants to see the CAOS items can register to access the ARTIST online tests, which would allow them to see the CAOS test items. We have discussed from to time WHEN we might release the items. However, at this time, the CAOS test is being used by a large enough number of instructors that we would prefer to not have the items published.

Thank you for your understanding.

Bob

On Thu, Mar 6, 2014 at 6:56 PM, Valorie Zonnefeld <Valorie.Zonnefeld@dordt.edu> wrote:

Bob,

Thank you for your support of my research. I plan to do an online administration through the ARTIST website. I do not have IRB approval yet, but plan to pursue it after I defend my proposal in the next month or so. I will pass the approval on to you once it is complete.

My committee has asked that I include the instruments that I am using in the appendix. Do you mind if I do so with the CAOS? I understand if you prefer not to have the instrument openly published.

Val

From: Robert delMas [mailto:delma001@umn.edu]

Sent: Thursday, March 06, 2014 6:51 PM

To: Valorie Zonnefeld

Subject: Re: CAOS permission

Dear Val:

You are welcome to use CAOS test for your research. The primary purpose for the development of the CAOS instrument was to support research. So you have our permission.

Are you planning to administer it as a paper-and-pencil test or to administer it online through the ARTIST website? If online, and you want access to the item level responses of students, I will need evidence of approval of your study from your IRB.

Best,

Bob delMas

+++

Robert C. delMas, Ph.D.

Associate Professor

Quantitative Methods in Education

Department of Educational Psychology

University of Minnesota

168 Education Sciences Building

56 East River Road

Minneapolis, MN 55455

On Thu, Mar 6, 2014 at 6:39 PM, Valorie Zonnefeld <Valorie.Zonnefeld@dordt.edu> wrote:

Dr. del Mas

I'm writing to request permission to use the Comprehensive Assessment of Outcomes in a First Statistics course instrument in research that I will be conducting for my dissertation. I am a doctoral student at the University of South Dakota and a professor at Dordt College in Sioux Center, Iowa. The topic of my dissertation is the role that students' mindsets play in their attitudes and statistical mastery using the theoretical framework from Carol Dweck. I would like to use the CAOS instrument to assess students’ levels of statistical literacy and understanding both at the beginning and end of the course.

Thank you for your attention and response,

Val

Appendix N

TMIS Permission

-----Original Message-----
From: Carol S Dweck [mailto:dweck@stanford.edu]
Sent: Tuesday, February 11, 2014 9:34 PM
To: Valorie Zonnefeld
Subject: Re: Permission Requested

Hi Valorie,

I'm attaching a copy of the Theory of Math measure we've used in our research. I wish you the best with your study.

Warm regards,
Carol Dweck

Lewis & Virginia Eaton Professor
of Psychology
Department of Psychology
Stanford University
Jordan Hall, Bldg. 420
Stanford, CA 94305

----- Original Message -----
From: "Valorie Zonnefeld" <Valorie.Zonnefeld@dordt.edu>
To: dweck@stanford.edu
Sent: Tuesday, February 11, 2014 3:16:15 PM
Subject: Permission Requested

Dr. Dweck,
I am writing to request permission to use and slightly alter the Theories of Intelligence Scale -Self-Form for Adult (Dweck, 1999, p. 178). I plan to research the role of incremental mindset training in introductory statistics classes in the fall, 2014 semester at Dordt College. To do so, I want to gain an understanding of the students' mindsets towards mathematics. Given the evidence of domain specificity for theories of intelligence and the suggestion by Calisto to use a domain-specific intelligence scale, I suggest the attached instrument. The wording remains virtually the same as the original instrument with the inclusion of 'mathematics' and 'mathematical' at appropriate points to get an assessment of students' mindset towards mathematics specifically.

Thank you for your consideration,
Val

Appendix O

SATS© Permission

From: Candace [mailto:cschau@comcast.net]

Sent: Wednesday, March 12, 2014 4:23 PM

To: Valorie Zonnefeld

Subject: RE: Permission Requested

Hi, Val,

Sorry it has taken me some time to reply. I have had guests.

Thanks for your interest in using my SATS©. If you have funding, I charge a small licensing fee for use of the SATS© (to support our continued work studying students' attitudes). If you don't have funding, I always hope that you can find some money within your institution to help with our research. If not, then you can use the SATS© free for one year. At the end of your year, contact me again if you would like to continue to use my measure. I do require that you send/e-mail me a copy of anything you write that includes information about your use of the SATS©. Also, when you use the SATS© or write about it, you need to indicate that I hold the copyright.

You need to use all of the items that comprise each attitude component on the SATS© (and I encourage you to use the other items too). If you want to omit or change any of those items, you will need to contact me again. Scores from the SATS© attitude components using all of the items have been carefully validated on postsecondary students with a wide variety of characteristics taking statistics in a large number of institutions both within and outside of the US. That validation work does not apply to altered items, individual items or to incomplete components. Also, it is not appropriate to use a "total" attitude score. You are welcome to change the demographic and academic items to fit your circumstances.

You can find references and scoring information on my web site. I have attached the pretest and posttest versions of the SATS©.

I wish you the best of luck with your work. Your project sounds interesting.

Candace

Candace Schau, PhD

CS Consultants, LLC

505-292-3567

www.evaluationandstatistics.com

From: Valorie Zonnefeld [mailto:Valorie.Zonnefeld@dordt.edu]

Sent: Saturday, March 08, 2014 6:34 AM

To: cschau@comcast.net

Subject: Permission Requested

Dr. Schau,

I am writing to request permission to use the Survey of Attitudes Towards Statistics© (SATS-36) instrument in research that I will be conducting for my dissertation. I am a doctoral student at the University of South Dakota and a professor at Dordt College in Sioux Center, Iowa. The topic of my dissertation is the role that students' mindsets play in their attitudes and statistical mastery using the theoretical framework from Carol Dweck. I would like to use the CAOS instrument to assess students' levels of statistical literacy and understanding both at the beginning and end of the course.

Thank you for your attention and response,

Val

Appendix P

Intervention Design Permission

From: Quintin Cutts [mailto:Quintin.Cutts@glasgow.ac.uk]

Sent: Friday, June 27, 2014 11:15 AM

To: Valorie Zonnefeld

Subject: Re: Mindset Training

Hi there Val,

You are welcome to use any parts of the mindset treatment that I designed in your work.

I just looked at the Cosby show clip that you passed on - it's good! It is like LEM, yes!

Best of luck with your work,

Cheers, Quintin.

Quintin Cutts

School of Computing Science

University of Glasgow

Glasgow G12 8RZ

+44 (141) 330 5619

On 27 Jun 2014, at 16:52, Valorie Zonnefeld <Valorie.Zonnefeld@dordt.edu>

wrote:

My dissertation proposal has been approved, but I should ask formally for permission to use parts of the mindset treatment that you shared earlier. Are you willing to allow the use of parts of the treatments that you designed? You will receive acknowledgement for your material.

Thanks,

Val

From: Valorie Zonnefeld

Sent: Thursday, February 27, 2014 12:48 PM

To: 'Quintin Cutts'

Subject: RE: Mindset Training

Thanks for your reply and no need to apologize for timeliness. I totally understand the demands of academia….thus my slow reply. The interventions that you shared are wonderful and I plan to implement aspects of them in my research this fall. My dissertation proposal includes multiple references to your work to justify my design and treatment. Thanks again!

You are correct that learning statistics is like acquiring a new language. Lalonde and Gardner (1993) made this exact argument. I briefly examined the paper on Learning Edge Momentum that you shared. It makes a lot of sense and really draws on a practical application of mindsets. It made me think of an old TV show. It's loosely connected to the ideas, but I'll attach the link below in case you are interested. It's a 1 minute clip from the Cosby Show. In the episode Theo, the son, is getting poor grades and frustrated because he crams so hard the night before exams while his friends barely study and get good grades. The father, Bill, uses the analogy of a plane to explain why his friends seem to be studying less, but yet receiving better grades. I think the video could also describe the concept of Learning Edge Momentum.

http://www.youtube.com/watch?v=6veFShCYQZw&feature=youtu.be

Thanks again for your response. If it's still valuable, I can take a more in depth examination of the Learning Edge Momentum paper this summer.

Val

Lalonde, R. N., & Gardner, R. C. (1993). Statistics as a second language? A model for predicting performance in psychology students. *Canadian Journal of Behavioural Science/Revue canadienne des sciences du comportement*, *25*(1), 108-125. doi: 10.1037/h0078792

From: Quintin Cutts [mailto:Quintin.Cutts@glasgow.ac.uk]

Sent: Thursday, February 13, 2014 8:19 PM

To: Valorie Zonnefeld

Subject: Re: Mindset Training

Dear Val,

Sorry for the delay in getting back to you on this.

I have just put the teaching materials, the crib sheet and wiki, and also a YouTube link for a video explaining our feedback sheet and the rubric described in the paper up on my home page - you'll find them under Innovations in Learning and Teaching or something like that. http://www.dcs.gla.ac.uk/~quintin

I can imagine that Stats is very similar to Computing Science - there's a whole new language to learn, and also I suspect the material is highly interconnected - meaning that it is hard to operate effectively unless all the concepts are understood. Very easy to develop a fixed mindset.

If you have time, I'd be interested in your thoughts on a paper about a concept called Learning Edge Momentum, postulated by a CS academic, Antony Robbins, attempting to explain the high failure rates in CS. Given that I believe non-majoring Stats students struggle with Stats, I was wondering if you thought Learning Edge MOmentum might be a good explanation for the difficulty. Robbins suggests that Stats might have similar characteristics to CS.

I've attached the paper, in case you have time to read it.

best regards,

Quintin.

Quintin Cutts

School of Computing Science

University of Glasgow

Glasgow G12 8RZ

+44 (141) 330 5619

On 23 Jan 2014, at 03:15, Valorie Zonnefeld <Valorie.Zonnefeld@dordt.edu> wrote:

Greetings! I am writing about your research on mindsets. I am a professor at Dordt College in Sioux Center, Iowa pursuing my doctorate at the University of South Dakota. I plan to research the role of mindset training on undergraduate students attitudes and achievement in introductory statistics for my dissertation. As I prepare for the study, I am curious what you used for mindset training and if you were pleased with it.

Thanks so much for your reply,

Val

Appendix Q

Host School Institutional Review Board Approval

DORDT COLLEGE

Institutional Review Board

Date: April 4, 2014

To: Valorie Zonnefeld, Principal Investigator

From: Dr. Kathleen VanTol, Chair, Dordt College Institutional Review Board

Re: IRB Project – Dissertation: Mindset, attitude, and achievement in undergraduate statistics courses

This letter serves as confirmation that your research project entitled "Mindset, attitude, and achievement in undergraduate statistics courses" has been **approved** under the **expedited** category of review by the Institutional Review Board of Dordt College. You many now begin to implement the research as described in the application.

Please note that you may only conduct this research exactly in the form it was approved. You must seek board approval for any changes in this project. In addition, if there are any unanticipated adverse reactions or unanticipated events associated with the conduct of this research, you should immediately suspend the project and contact the Chair of the Institutional Review Board for consultation.

The Board wishes you success in the pursuit of your research goals.

Kathleen M. VanTol

498 Fourth Avenue NE Sioux Center, Iowa 51250-1606 Phone 712-722-6000

Appendix R

Institutional Review Board Approval

UNIVERSITY OF
SOUTH DAKOTA

June 16, 2014

The University of South Dakota
414 E. Clark Street
Vermillion, SD 57069

PI: Kevin Reins, Ph.D. **Student PI:** Valorie Zonnefeld
Project: 2014.147 - Mindsets, Attitudes, and Achievement in Undergraduate Statistics Courses
Review Level: Exempt 1 & 2 **Risk:** No More than Minimal Risk
USD IRB Initial Approval: 6/16/2014
Approved items associated with your project:
Survey
Cover Letter

The proposal referenced above has received an Exempt review and approval via the procedures of the University of South Dakota Institutional Review Board.

Annual Continuing Review is not required for the above Exempt study. However, when this study is completed you must submit a Closure Form to the IRB. You may close your study when you no longer have contact with the subjects and you are finished collecting data. You may continue to analyze the existing data on your closed project.

Prior to initiation, promptly report to the IRB, any proposed changes or additions (e.g., protocol amendments/revised informed consents/ site changes, etc.) in previously approved human subject research activities.

The forms to assist you in filing your: project closure, continuation, adverse/unanticipated event, project updates /amendments, etc. can be accessed at http://www.usd.edu/research/research-and-sponsored-programs/irb-application-forms-and-templates.cfm.

If you have any questions, please contact: humansubjects@usd.edu or (605) 677-6184.

Sincerely,

Sandra Ellenbolt

Sandra Ellenbolt, JD
Director, Office of Human Subjects Protection
IRB Member
University of South Dakota
Institutional Review Boards
(605) 677-6184
LJT00000004925