GROWTH MINDSET AND TASK VALUE INTERVENTIONS

IN COLLEGE ALGEBRA

by

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A dissertation submitted to the Graduate Council of
Texas State University in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
with a Major in Developmental Education
May 2018

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DEDICATION

I dedicate this dissertation to Duy and Alex.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank the Father, Son, and Holy Spirit for continually guiding me and the Blessed Virgin Mary for her prayers. I also thank my family and friends for their support. Next, I would like to thank and acknowledge my committee members—Drs. Taylor Acee, Jodi Holschuh, Eric Paulson, and Alexander White—who have directed me throughout this entire dissertation process as well as the faculty of the developmental education program who have shared their expertise with me throughout the years. I especially thank Dr. Taylor Acee, who profoundly influenced me through a variety of capacities. As an advisor, he supported and guided me through difficult situations; as a boss, he laid the foundation for my success by modeling best practices in research; and as my committee chair, he increased the rigor of my dissertation through his insightful feedback. Only through observing and working with Dr. Acee as he expertly ran his studies and analyzed his data was I able to complete my own dissertation study. Beyond his academic support, I also truly appreciate his enthusiasm, positive attitude, and continual belief in my ability to succeed. I could not have had a better mentor than the one I found in Dr. Acee. Last but not least, I want to thank my cohort members and classmates for their camaraderie. I especially thank Darolyn Flaggs for walking with me; her presence and prayers brightened my journey, eased the burden, and provided much-needed moral support and encouragement. My accomplishments have been a result of the support I have received from my community, and I thank everyone who has been involved in helping me reach my goals.

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LIST OF ABBREVIATIONS

Abbreviation	Description
C	Cost
ENUV	Endogenous Utility Value
GPA	Grade Point Average
IB	Intelligence Beliefs
M	Mean
PA	Performance Avoidance Goals
PI	Personal Importance
SD	Standard Deviation
SE	Self-Efficacy

ABSTRACT

Growth mindset interventions and task value interventions have been effective in raising student academic performance, particularly for students who have low prior achievement. These interventions, however, have not been tested in combination with each other or individually in a college algebra setting. This study tested a growth mindset intervention, a task value intervention, and a combined growth mindset and task value intervention on students (N=426) in college algebra to determine the interventions' effects on measures related to intelligence beliefs and value perceptions as well as on final course score. This study found that the growth mindset intervention positively affected intelligence beliefs, and the task value intervention increased endogenous utility value. Furthermore, the combined growth mindset and task value intervention was effective in raising both intelligence beliefs and endogenous utility value. Although these interventions affected their targeted psychological outcomes, they did not increase academic performance on final course score. Implications of these findings are discussed.

I. INTRODUCTION

Many students do not pass their introductory mathematics courses in college (RTI International, 2015). In both developmental and college-level courses, interventions have focused on altering the delivery (Herron, Gandy, Ye, & Syed, 2012; Hopf, Sears, Torres-Ayala, & Maher, 2015; Ichinose & Clinkenbeard, 2016; Reyes, 2010; Rutschow & Schneider, 2011) and content (Carnegie Foundation for the Advancement of Teaching, 2016; Mireles, Acee, & Gerber, 2014) of these mathematics classes in efforts to improve student success. Few interventions, however, have concentrated on changing the perception of college students in mathematics. Social psychological interventions in education are "interventions designed to change students' thoughts and feelings in and about school" (Yeager & Walton, 2011, p. 276). Because many students believe that they will never be good at math (Boaler, 2016) and fail to see value in what they are learning (Luttrell et al., 2010), this research study addressed these negative attitudes through a combination of two social psychological interventions. The first intervention was a growth mindset intervention, which informed students about the malleability of intelligence, and the second intervention was a task value intervention, which shared about the potential value of learning mathematics to students. Although robust lines of research have emerged on the positive effects of growth mindset interventions (e.g., Paunesku et al., 2015; Yeager et al., 2016) and task value interventions (e.g., Acee & Weinstein, 2010; Harackiewicz, Canning, Tibbetts, Priniski, & Hyde, 2015), especially for struggling students, these interventions have not been examined in combination or tested in postsecondary college algebra courses.

Incoming students often take college algebra courses as their first credit-bearing mathematics course (Adelman, 2004), and nationally, the passing rate for college algebra has been estimated to be around 50% to 60% (Herriott, 2006). At the institution where this study was conducted, the passing rate for college algebra ranged from 58.2% to 63.5% between 2010 to 2015. With an experimental, repeated measures design, this study tested the effectiveness of a growth mindset intervention, a task value intervention, and a combination of the two interventions in college algebra courses. The research questions of this study were:

1) Do the growth mindset, task value, and combination interventions produce changes in students' intelligence beliefs, self-efficacy, and value perceptions over time from pre-survey to post-survey when compared to a control group?
2) In regard to changes in students' intelligence beliefs, self-efficacy, and value perceptions over time (i.e., from pre-survey to post-survey), do students benefit differently from the growth mindset, task value, and combination interventions based on demographic variables (i.e., gender, race/ethnicity, and first-generation status) and pre-survey measures (i.e., test 1 grades, initial intelligence beliefs, and initial value perceptions) when compared to a control group?
3) Do the growth mindset, task value, and combination interventions have positive effects on final course score when compared to a control group?
4) In regard to final course score, do students benefit differently from the growth mindset, task value, and combination interventions based on their demographic variables (i.e., gender, race/ethnicity, and first-generation status) and pre-survey

measures (i.e., test 1 grades, initial intelligence beliefs, and initial value perceptions) when compared to a control group?

To answer these research questions, a study was conducted in four sections of college algebra at a large, public university in the southwestern United States. Because the participants came from four sections of college algebra, stratified random assignment to groups was used; students were stratified according to class section and then randomly assigned to four groups: growth mindset, task value, combination, and control. Before completing any interventions, students took a pre-survey that included measures of initial intelligence beliefs, self-efficacy, value perceptions, and demographic information. Later, each participant completed two online activities that were specific to the group to which they were assigned. At the end of the study, students took a post-survey that included repeated measures of intelligence beliefs, self-efficacy, and value perceptions, and grades were obtained from the instructors. The effects of the growth mindset, task value, and combination interventions on intelligence beliefs, self-efficacy, value perceptions, and academic performance were examined using multiple regression analyses. In addition, the data were analyzed to see whether these interventions interacted with other study variables, such as demographics.

By conducting this research in college algebra classrooms, the usefulness of these types of interventions within introductory college mathematics courses could be established. Furthermore, this research added to the body of social psychological research by testing a combined intervention in which two different kinds of social psychological interventions, one addressing intelligence beliefs and the other addressing value perceptions, were tested together in one study.

Definitions of Key Concepts and Terms

To clarify the meaning of key concepts and terms pertaining to this study, a list of operationalized definitions is included below:

1) College Algebra – a credit-bearing, college-level course covering linear and quadratic equations, inequalities, word problems, functions, logarithms, systems of equations, and other college algebra topics.
2) Growth Mindset Intervention – an intervention that included growth mindset messages and writing activities. The messages described how the brain is a muscle, how the brain grows in neural connectivity as a person learns new concepts, how believing in a growth mindset can have advantages, and how effort and appropriate strategies can help in learning math. At the end of these messages, participants were asked to write a letter to future students summarizing the growth mindset information.
3) Task Value Intervention – an intervention that included a rating activity with task value messages and two writing activities. The participants read six reasons describing why college algebra could be useful to them and rated how much they believed in each reason. These reasons focused on the usefulness of college algebra in developing problem solving and critical thinking skills, modeling real-life scenarios, preparing students to learn new quantitative skills in future situations, learning math skills needed in future classes, building positive student habits, and obtaining a college degree. The participants then wrote a letter to future college algebra students detailing the reasons why learning college algebra was personally relevant to them. Last,

participants also wrote a reflection about whether learning college algebra could be beneficial to others, such as their friends, family, community, or society.

4) Combination Intervention – an intervention that asked participants to complete both the growth mindset and the task value interventions.
5) Intelligence - an individual's capacity for communication, planning, learning, understanding, reasoning, problem solving, and abstract thought (Goldstein, 2015).
6) Intelligence Beliefs – individuals’ beliefs about the malleability of intelligence. Two self-theories exist: the incremental theory and the entity theory. The incremental theory posits that intelligence is malleable while the entity theory maintains that intelligence is fixed. Those who believe in the incremental theory are said to have a 'growth mindset' whereas those who believe in the entity theory are said to have a 'fixed mindset' (Yeager & Dweck, 2012).
7) Value Perceptions – individuals' beliefs about why they want to complete a task. According to expectancy-value theory, value includes four subcomponents: intrinsic value, utility value, attainment value, and cost. Intrinsic value refers to the enjoyment or intrinsic interest in a task, utility value refers to the usefulness of a task to individuals' current and future goals, attainment value refers to the importance of doing well on a task and ties in to individuals' self-identity, and cost refers to the perceived negative aspects of

participating in a task (Wigfield & Eccles, 2002). In this study, endogenous utility value, attainment value, and cost were examined as value outcomes.

8) Endogenous Utility Value – the perceived usefulness of the skills and knowledge gained in a course for the attainment of future goals (Husman, Derryberry, Crowson, & Lomax, 2004).
9) Self-Efficacy – individuals' judgments of their capabilities to complete actions at a certain level of performance (Bandura, 1986).

Organization of Dissertation

This dissertation follows a traditional five-chapter format. The first chapter of this dissertation introduces the study, and the second chapter focuses on the literature review, which discusses the theoretical framework for this study, social psychological interventions, theories and interventions related to beliefs about intelligence and value perceptions, and gaps in research related to intelligence and value interventions. The third chapter describes the methods of the study, which include the research questions and hypotheses, the procedures, the participants, the measures, and the data collection methods. Next, the fourth chapter gives the results of the study and covers the preliminary and primary analyses, and the fifth chapter consists of a discussion of the results, limitations of the study, directions for future research, and conclusions.

Chapter Summary

This chapter introduced social psychological interventions, particularly growth mindset and task value interventions, and revealed the lack of studies on the effects of combined social psychological interventions as well as the effects of social psychological interventions within college algebra courses, which tend to have high failure rates.

Therefore, the goal of this dissertation study was to examine whether a growth mindset, a task value, and a combined growth mindset and task value intervention could change students' intelligence beliefs, self-efficacy, and value perceptions as well as increase academic performance of students in college algebra. The study's research questions, a list of operationalized definitions, and a description of the dissertation's organization were also described in this chapter. In the next chapter, a review of literature will explain social psychological interventions, the theories and interventions related to growth mindsets and task values, and the gaps in current intervention research.

II. REVIEW OF THE LITERATURE

In the last decade, a surge of research on social psychological interventions has emerged with the goal of helping students in various academic disciplines. Social psychological interventions in education are “interventions designed to change students’ thoughts and feelings in and about school” (Yeager & Walton, 2011, p. 276), and they vary in nature depending on their goals and tasks. Some ask students to reflect on their possible future selves (Oyserman, Bybee, & Terry, 2006), their currently held values (Cohen, Garcia, Purdie-Vaughns, Apfel, & Brzustoski, 2009), their attributions for academic failure (Wilson & Linville, 1982), their perceptions of intelligence (Blackwell, Trzesniewski, & Dweck, 2007), their valuations about the personal relevance of academic tasks (Hulleman & Harackiewicz, 2009), or their ideas about positive and negative aspects of academic task engagement (Oettingen, Pak, & Schnetter, 2001). By completing these reflective tasks, researchers have found positive intervention effects in regard to academic performance and attitude change. For example, students who learn about the malleability of intelligence have been shown to endorse positive intelligence beliefs, achieve better grade, and show increased motivation in the classroom (Blackwell et al., 2007).

Overall, social psychological interventions seem to be effective for two reasons. First, these interventions have been found to be successful because they attempt to change students’ subjective experiences in school (Yeager & Walton, 2011). For example, when students fail a mathematics exam, they may believe that they simply lack the necessary innate ability to learn math. However, after discovering that intelligence is malleable, students may begin to attribute failure to lack of effort, which can be remedied. Changing students' subjective understanding of failure can thus change what students will do when faced with setbacks in the future. Second, social psychological interventions seem to work because they use psychologically wise delivery methods. Rather than merely telling students about the malleability of intelligence or the value of a course topic, interventions normally require students to internalize the message through actions, such as writing (Aronson, Fried, & Good, 2002; Canning & Harackiewicz, 2015) or creating webpages (Blackwell et al., 2007). In addition, rather than targeting a population and letting them know that they are undergoing interventions for particular reasons, the interventions normally are administered without mentioning specific desirable outcomes. Therefore, students do not feel controlled or stigmatized by these interventions (Yeager & Walton, 2011). Social psychological interventions are hypothesized to be effective because they change students' subjective experiences and they help students internalize messages, and these mechanisms work within a social cognitive framework.

Theoretical Framework

Social cognitive theory developed partly in response to the inadequacy of behavior theories, which focused on analyzing human behavior in nonsocial situations. During the early twentieth century, behavior theories dominated psychology. Behavior theories disregarded internal thoughts and feelings as explanations for behaviors and believed that observable actions and behaviors were direct functions of environmental events. Cognitive theories, however, emphasized the importance of examining mental processing of information and beliefs to understand human behavior (Schunk, Meece, & Pintrich, 2014). Specifically, Bandura's (1986) social cognitive theory contributed to this understanding by positing that individuals are driven by the interactions of behavioral, personal, and environmental factors. This perspective was different from behavior theories because it asserted that along with the environment, personal factors can affect behavior, and in turn, behavior can also affect personal and environmental factors. This understanding led to Bandura's (1986) model of triadic reciprocality, which emphasized the reciprocal nature of the interactions between behavioral, personal, and environmental factors.

Examples of the behavior-environment interaction, the behavior-person interaction, and the person-environment interaction can be seen with students in a classroom setting (Schunk et al., 2014). Teachers can direct students to attend to a lesson, and students may respond by raising their eyes and focusing on the topic at hand (environment affecting behavior). If students begin to look around the classroom and talk to their classmates, teachers may change up their delivery method to recapture students' attention (behavior affecting environment). Students' personal factors, such as cognition or interest, can affect behavior as well, and behavior can affect personal factors. If teachers present material that relates to students' hobbies and interests, students may engage in a lesson more by asking additional questions and actively participating in discussion (personal factor affecting behavior). As students participate more in the lesson, they may increase their knowledge and interest in the topic (behavior affecting personal factor). Personal factors can also influence environment, and environment can affect personal factors. If students are feeling apprehensive about learning a certain topic, teachers may alter their lesson in response (personal factor affecting environment). Furthermore, if teachers teach the lesson in a way that is understandable and clear, students may feel less apprehensive by the end of the lesson (environment affecting personal factor). Bandura's (1986) social cognitive theory explains how personal, behavioral, and environmental factors influence each other, and the theory is useful in understanding how social psychological interventions work.

In relation to growth mindset and task value interventions, social cognitive theory is relevant because how people construe, interpret, and process an academic environment and situation can affect their behaviors (Dweck, 1986). Both the growth mindset and task value interventions aim to affect a person's cognition in interpreting a situational event, which may then influence their behavior. For example, when a teacher presents difficult, seemingly irrelevant information in class, students who believe that they will eventually be able to understand the difficult information or students who can find value in the information may attend to the information better and engage more deeply in the learning process. These students may choose to ask more questions, and their behavior can affect others in their environment. Growth mindset and task value interventions can potentially affect cognition and personal factors, which in turn can affect students' behavior and environment. Situated in this theoretical framework, this literature review will first discuss theories of intelligence along with growth mindset interventions and then examine expectancy-value theory along with task value interventions.

Theories of Intelligence

Although there is evidence to support that intelligence is malleable (Blackwell, Rodriguez, & Guerra-Carrillo, 2015), not all people believe that their intelligence can change. This section will discuss the nature of intelligence, the ways in which people view intelligence, growth mindset interventions and their effect on academic achievement, and critiques of theories of intelligence research.

Intelligence

While the general public has a broad understanding of intelligence, there is no scholarly consensus on a formal definition. In fact, according to Sternberg (as cited in Goldstein, 2015), when intelligence is "viewed narrowly, there seem to be almost as many definitions of intelligence as there are experts asked to define it" (p. 3). Regardless of the differences in formal scholarly definitions, the concept of intelligence typically relates to an individual's capacity for communication, planning, learning, understanding, reasoning, problem solving, and abstract thought (Goldstein, 2015).

There is evidence to support the notion that intelligence, as measured by intelligence tests, can change over time (Blackwell et al., 2015). For example, individuals who attend school and training programs can increase their score on the Wechsler Intelligence Scale, which is an assessment of intelligence (Brehmer, Westerberg, & Backman, 2012; Ceci, 1991). In fact, a physiological change occurs within the brain when an individual is learning. The brain is made up of billions of cells called neurons, which communicate with each other to coordinate physical and mental tasks. When individuals practice skills, such as visual-motor skills (Draganski et al., 2004) or reasoning skills (Mackey, Miller-Singley, & Bunge, 2013), their brain scans showed increased connectivity between neurons compared to individuals who did not practice these skills. The ability of the brain to increase and decrease in neural connectivity is called neuroplasticity. As individuals learn and practice new skills, both intelligence and the brain change over time.

Self-Theories of Intelligence

Although research has shown that intelligence can increase over time (Brehmer et al., 2012; Ceci, 1991), individuals hold different self-theories about whether intelligence is malleable or not. Self-theories are people's beliefs about themselves, and these beliefs tend to be implicit (Dweck, 2000). Self-theories include beliefs about a wide range of personal characteristics, such as intelligence (Yeager & Dweck, 2012), athletic abilities (Biddle, Wang, Chatzisarantis, & Spray, 2003; Chen et al., 2008), body weight (Burnette, 2010), leadership abilities (Hoyt, Burnette, & Innella, 2012), human personality (Dweck, 2000), willpower (Job, Dweck, & Walton, 2011), and negotiation abilities (Kray & Haselhuhn, 2007). In regard to individuals' beliefs about the malleability of these personal characteristics, two implicit theories exist: the incremental theory and the entity theory. While some individuals adopt the incremental theory, which posits that personal characteristics are changeable, other individuals support the entity theory, which maintains that personal characteristics are fixed. Those who believe in the incremental theory are said to have a 'growth mindset' whereas those who believe in the entity theory are said to have a 'fixed mindset' (Yeager & Dweck, 2012).

In regard to intelligence, people with incremental views believe that intelligence is malleable whereas people with entity views believe that intelligence is fixed. Interestingly, people do not always have the same theory of intelligence in every domain. For example, individuals can have differing beliefs about the nature of general intelligence and the nature of mathematical intelligence; Shively and Ryan (2013) found that college algebra students tend to have more incremental views of general intelligence than of mathematical intelligence. Regardless of domain, people with incremental views of intelligence tend to have more positive motivational patterns whereas people with entity views of intelligence tend to have more negative motivational patterns in terms of goal orientation (i.e., people's reasons for engagement in achievement tasks), attributions (i.e., perceived causes behind success or failure), and behavior.

Goal orientation. Goal orientation refers to people's rationale for involvement in achievement tasks. The most common goal orientations are learning goals (also known as task-involvement or mastery goals; Ames, 1992; Nicholls, 1984) and performance goals (also known as ego-involvement goals; Nicholls, 1984). Those who have a learning goal typically focus on learning and mastering a task or skill whereas those who have a performance goal typically focus on proving their competence or ability (Schunk et al., 2014).

People with different implicit theories of intelligence tend to be associated with different types of goal orientations (Burnette, O'Boyle, VanEpps, Pollack, & Finkel, 2012; Dweck & Leggett, 1988; Mangels, Butterfield, Lamb, Good, & Dweck, 2006; Robins & Pals, 2002). People with growth mindset beliefs frequently view academic tasks as opportunities to develop and strengthen skills, which in turn could bolster their intelligence; therefore, they tend to focus on learning goals. However, people with fixed mindset beliefs tend to view academic tasks as tests of their ability that reflect their fixed level of intelligence. Consequently, people with fixed mindset beliefs tend to focus on performance goals in efforts to prove to others that they have a certain level of intelligence.

The relation between intelligence beliefs and goal orientation has been supported by various studies. For example, children with growth mindset beliefs were more likely to prefer classrooms tasks that were "hard, new, and different so I could try to learn from them" over tasks which were "fun and easy to do, so I wouldn't have to worry about mistakes" (Dweck & Leggett, 1988, p. 263). In addition, when Mangels et al. (2006) used event-related potentials to measure brain waves of students during a general intelligence test, Mangels et al. (2006) found that people with fixed mindset beliefs had increased activity in areas of the brain associated with concerns about proving their skills in relation to others. In addition, when people with fixed mindset beliefs received negative feedback about their performance, their brain scans revealed "less sustained memory-related activity . . . to corrective information" (p. 75), which implied that their focus was not on learning the skills but merely proving their ability when tested. These studies support the notion that people with growth mindset beliefs tend to have learning goals whereas people with fixed mindset beliefs tend to have performance goals. Not only do implicit intelligence beliefs relate to certain goal orientations, but they also are connected to particular attributions.

Attributions. Self-theories of intelligence can influence students' attributions, which are the perceived causes behind successes or failures (Weiner, 2010). For students who believe that intelligence is malleable, the perceived cause of failure tends to be lack of effort (Hong et al., 1999), which is within students' control; if these students increase their effort, they could potentially increase their intelligence. For students who believe that intelligence is fixed, the perceived cause of failure tends to be lack of ability. Because these students do not believe that intelligence or ability can improve because they are fixed characteristics, making this attribution can lead to negative affective reactions and helpless behavioral responses, which can lead to a decrease in self-esteem

(Robins & Pals, 2002). Believing in different implicit intelligence theories can lead to different attributions when faced with failure, which can lead to distinctive behavioral responses in academic situations.

Behavioral responses. Students with growth mindset beliefs and students with fixed mindset beliefs tend to respond to difficult academic situations differently. For example, students with fixed mindset beliefs are inclined to have negative behavioral responses that do not facilitate future success; Hong et al. (1999) found that students with low English proficiency who had fixed mindset beliefs were less interested in attending a remedial English course than students with low English proficiency who had growth mindset beliefs. Furthermore, negative behavioral responses can also occur when students are taught about fixed mindsets; after students were told that they performed below average on an intelligence test and were presented with an opportunity to either take a remedial tutorial or work on an unrelated task, students who learned about fixed mindsets were more likely than students who learned about growth mindsets to choose to work on the unrelated task (Hong et al., 1999). Similarly, in Nussbaum and Dweck's (2008) study, engineering students who did poorly on an engineering test and learned about fixed mindsets chose not to engage in a remedial tutorial whereas those who learned about growth mindsets chose to participate in the remedial tutorial.

In addition to not taking advantage of tutorials or remediation to build skills, students with fixed mindset beliefs tend to shy away from challenges (Dweck, 1986; Mueller & Dweck, 1998). Because students with fixed mindset beliefs deem that the results of each challenge determine whether they are smart or not, they prefer easier tasks over harder ones so that they can successfully complete the task and prove their intelligence. On the other hand, because students with growth mindset beliefs see challenges as an opportunity to learn, they desire more challenging tasks so that they can build their intelligence.

The behavioral responses of students with growth mindset beliefs are typically desirable in an academic setting; students will eventually face challenge in their educational career, and students who welcome challenge and seek help or remediation as needed may have better academic performance. To investigate the connection between intelligence beliefs and academic achievement, researchers conducted studies to test whether teaching students about growth mindset beliefs improved academic outcomes.

Growth mindset interventions and academic achievement. Many studies have been done to examine whether interventions that teach about growth mindsets improve academic performance. First, Blackwell et al. (2007) conducted a longitudinal study that examined four waves of students who completed seventh and eighth grade at a public school in New York City. Originally, these students had similar scores on a standardized mathematics test in the sixth grade. However, after two years in junior high school, students with growth mindset beliefs had significantly higher mathematics grades than students with entity beliefs. Seeing that growth mindset beliefs were associated with higher grades, Blackwell et al. (2007) conducted a follow-up, quasi-experimental study to see whether a growth mindset intervention could improve the grades and behaviors of junior high students. The researchers created eight 25-minute sessions where the intervention group learned about the incremental theory of intelligence whereas the control group learned about memory and academic topics of personal interest to the students. Blackwell et al. (2007) found that 27% of students in the experimental condition had a positive change in classroom motivational behavior compared to only 9% of the students in the control condition. In addition, they found that students in the experimental condition significantly outperformed students in the control condition by scoring 0.3 grade points higher on their mathematics grade point average at the end of their eighth-grade year.

Two other studies show the positive effects of growth mindset interventions for students in school. First, Good, Aronson, and Inzlicht (2003) conducted a study with seventh-graders from a rural Texas school where the students were randomly assigned to be in one of four conditions: incremental, attribution, combination, or control. Students in the incremental condition created a webpage that discussed the malleable nature of intelligence, students in the attribution condition discussed the common struggles of all seventh-grade students which will improve over time, students in the combination condition discussed the contents of both the incremental and attribution webpages, and students in the control condition discussed the perils of drug use. At the end of the year, Good et al. (2003) found that students in the control condition had a performance gap between the two sexes on a mathematics standardized test, but female students in the incremental, attribution, and combination conditions scored similarly to males. Second, Aronson et al.'s (2002) study tested whether learning about the malleability of intelligence could reduce stereotype threat among African American students at Stanford University. Their intervention consisted of students learning about an intelligence orientation and writing letters to fictitious middle school students to advocate for the intelligence orientation. Three groups composed of African American and Caucasian students participated in the study where one group was the treatment group and the other two groups were control groups. The treatment group learned and wrote letters about the malleability of intelligence, the first control group learned and wrote letters about multiple intelligences, and the second control group did not learn or write letters about an intelligence orientation at all. The African American students who were in the intervention group reported greater academic engagement and enjoyment and achieved higher grade point averages than their counterparts in the two control groups.

While all three of these studies (Aronson et al., 2002; Blackwell et al., 2007; Good et al., 2003) conducted an experiment within one school, Paunesku et al. (2015) examined whether growth mindset interventions were effective across 13 different high schools with 1,594 students. In this experiment, Paunesku et al. (2015) tested a growth mindset intervention, a sense-of-purpose intervention, and a combination of the two. In the growth mindset intervention, students read an article about the ability of the brain to grow through putting in effort and using effective strategies, and they were asked to summarize the information in a letter to future students. In the sense-of-purpose intervention, students were asked to reflect on what they wanted to contribute to society and how their current courses could help them achieve their goals. Each intervention lasted 45 minutes long, and they were delivered online. If students received a combination of the interventions, they received one 45-minute intervention about one topic, and two weeks later, they received another 45-minute intervention on the second topic. Paunesku et al. (2015) found that students who previously failed at least one core academic class or had a baseline GPA of 2.0 or less showed a significant increase in the number of courses they passed and in their GPAs if they received any of the interventions.

Yeager et al. (2016) replicated Paunesku et al.'s (2015) study and tested to see if a revised growth mindset intervention would lead to better results. First, Yeager et al. (2016) wanted to determine which characteristics in a growth mindset intervention were effective. They found that direct framing of the message, which told the students that the intervention was meant to help them directly, had smaller effects on changing intelligence orientations than indirect framing, which described how the interventions could help students in general. In addition, labeling and explaining the benefits of having a growth mindset led to stronger changes in mindsets than when benefits were not explained. These findings helped create a revised growth mindset intervention. To see whether the revised growth mindset intervention worked better than Paunesku et al.'s (2015) intervention, they conducted research at 69 different schools with 7,501 ninth graders in the United States. One group completed Paunesku et al.'s (2015) intervention while another group completed the revised intervention. Yeager et al. (2016) found that both interventions significantly changed intelligence orientations, but the revised intervention had a larger effect. In addition, the revised intervention was more effective at changing outcomes such as beliefs and short-term behaviors. Therefore, Yeager et al. (2016) took the revised intervention to 10 schools and tested 3,676 ninth graders to see if it would have a positive effect on grades. Similar to previous studies, Yeager et al. (2016) found that for low-achieving students, there was an increase in core course grades after completion of the revised growth mindset intervention. Yeager et al. (2016) hypothesized that these interventions tended to help low-achieving students because they could make higher increases with their grades; high-achieving students who were already making top grades had little room to improve. Furthermore, Yeager et al. (2016)

postulated that high-achieving students may be taking on more challenging tasks in school, which may help them learn more but would not help improve their grades.

Overall, there is strong evidence that growth mindset interventions help students make better grades, but these effects are usually limited to certain groups of students; Good et al. (2003) only found positive effects among women, Aronson et al. (2002) only found positive effects among African-American students, and Paunesku et al. (2015) and Yeager et al. (2016) only found positive effects among lower-achieving students. Although only certain groups of students seem to benefit, these studies provide evidence that growth mindset interventions can be successful in influencing academic outcomes.

Critiques of theories of intelligence research. While many research studies have supported the efficacy of growth mindset interventions on improving academic outcomes for certain students, other research studies have discovered that having a fixed mindset can be beneficial in particular situations. For example, Burns and Isbell (2007) conducted a study on women with high math ability where some held fixed mindset beliefs and others held growth mindset beliefs. In their study, the women read a message supporting fixed mindset beliefs before taking a math test. Under this condition, women who had fixed mindset beliefs performed better than women who had growth mindset beliefs. Burns and and Isbell (2007) believed that because these women had high math ability, the message supporting fixed mindset beliefs reminded the women of their high intelligence and helped them performed better on the math test. Furthermore, Park and Kim (2015) found additional evidence that fixed mindset beliefs could be beneficial. These researchers had all participants engage in a task that was impossible to complete, so after participants attempted the task, they were told that they failed at the activity.

When participants were given a different task along with instructions that the next task measured a different ability, students with fixed mindset beliefs performed better than students with growth mindset beliefs; this was because when students with a growth mindset approached the second task measuring a different ability, they had more self-critical thoughts about their lack of effort than students with a fixed mindset, and these self-critical thoughts hindered their performance on the second task. Although these studies support that having fixed mindset beliefs can be helpful, both of these studies were done in the laboratory where certain conditions were imposed on students. First, Burns and Isbell (2007) exposed their high-ability math participants to a fixed mindset message before an exam, which bolstered their beliefs in their high math ability and helped their performance. When Burns and Isbell (2007) conducted the same study on women with mixed math abilities, they found that the fixed mindset message was not effective in raising math test performance at all. Second, Park and Kim (2015) set students up for failure by giving them an impossible task, but the participants did not know that the task was impossible to complete. This situation led students to make incorrect attributions of why they failed. Intelligence beliefs are related to attributions (Hong et al., 1999), and leading students to make incorrect attributions may not truly reflect how students would perform in a classroom if students were given accurate feedback. More importantly, neither studies noted any harm in sharing growth mindset beliefs with students who held either fixed or growth mindset beliefs. Therefore, because of the lack of harm of growth mindset messages and because of the previous success of growth mindset interventions in the classroom (e.g., Blackwell et al., 2007; Paunesku et al., 2015), it is reasonable to continue to test the effectiveness of growth mindset interventions in different classroom settings. In addition, because combination interventions (Good et al., 2003; Paunesku et al., 2015) have yet to pair growth mindset interventions with task value interventions, it is reasonable to attempt to combine these social psychological interventions to examine their effects on academic performance.

Task Value Interventions

Many students believe that they will never be good at math (Boaler, 2016) and that learning math has no real-life value (Luttrell et al., 2010). Growth mindset interventions could be used to challenge the first misconception, and task value interventions could be used to combat the second misconception. Task value interventions help students reevaluate the value of learning particular course material, and they are rooted in expectancy-value theory. This section will describe expectancy-value theory, task value interventions, and critiques about the task value research.

Expectancy-Value Theory

Contemporary expectancy-value theory is based on the work of Wigfield and Eccles (2002). In their model, expectancy and value affect motivation and achievement behavior. First, expectancy refers to individuals' beliefs about whether they can successfully complete a task, and expectancy beliefs include expectations for success and self-concepts of abilities. In earlier concepts of their theory, Eccles and Wigfield (2002) proposed that two types of expectancy beliefs existed: ability and expectancy. Ability beliefs reflected individuals' beliefs about their abilities in a given domain whereas expectancy beliefs reflected individuals' beliefs about their ability to complete a future task. However, these two beliefs had high correlations with each other and could not be teased apart empirically, so current expectancy measures include both ability and expectancy-belief items which comprise general expectancy beliefs.

Expectancy beliefs overlap with other concepts in the field of motivation, such as self-efficacy and self-theories of intelligence. For instance, Eccles and Wigfield (2002) connected Bandura's (1997) self-efficacy theory with expectancy beliefs. Self-efficacy is defined as "people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances" (Bandura, 1986, p. 391), which is similar to Wigfield and Eccles's (2002) self-concept of abilities under the expectancy domain. However, Bandura's idea of self-efficacy is more specific and situational than Wigfield and Eccles's idea of self-concept of abilities; whereas self-concept of ability can refer to general judgment of one's ability, such as whether one can do well in school, self-efficacy specifically refers to one's judgment about particular tasks and situations, such as whether one can do well on a midterm in college algebra. Measures assessing Eccles and Wigfield's expectancies for success are similar to Bandura's measures of self-efficacy (Eccles & Wigfield, 2002) with the exception that measures of self-efficacy tend to focus on specific situations at a given time whereas self-concept measures tend to focus on more general situations (Schunk et al., 2014).

Not only does self-efficacy have connections with expectancy beliefs, but self-theories of intelligence also share some commonalities with expectancy beliefs (Wigfield, 1994). Expectancy beliefs include ability beliefs, and when students view ability as the capacity to succeed on a task, then these students are seeing ability as a stable trait that cannot be changed. Wigfield (1994) noted that this perspective of ability as a capacity to succeed is similar to the entity view of intelligence. However, while there are conceptual connections between the ability and intelligence beliefs, the measures for these beliefs do not seem to overlap. Measures about ability beliefs ask students about their belief in their ability to do well in a situation (e.g., "How well do you think you will do in your math course this year?"; Eccles, O'Neill, Wigfield, 2005, p. 246) whereas measures about intelligence beliefs ask students about their belief in regard to the nature of intelligence (e.g., "You have a certain amount of [math] intelligence, and you really can't do much to change it."; Dweck, 2000, p. 178). Interestingly, while Diseth, Meland, and Breidablik (2014) have empirically shown that intelligence beliefs and self-efficacy beliefs are distinct but correlated concepts, a lack of studies explore the empirical relationship between intelligence and ability beliefs. While expectancy beliefs, as defined by Eccles and Wigfield (2002), are conceptually related to self-efficacy and self-theories of intelligence, expectancy beliefs are typically extensively studied as its own concept apart from self-efficacy and self-theories of intelligence.

Expectancy beliefs are typically studied in domain-specific areas, and they strongly predict achievement and task involvement; individuals who have stronger beliefs in their competence tend to have higher scores on achievement measures, such as standardized test scores and final course grades, and tend to put in more effort and persist longer on various tasks (Wigfield & Eccles, 2002). In addition, expectancy beliefs also predict the use of cognitive strategies and metacognitive strategies; individuals with better perceptions of their competence tend to use more cognitive and metacognitive strategies (Schunk et al., 2014). Last, expectancy beliefs are believed to positively related to values (Wigfield & Eccles, 2002).

Value refers to individuals' beliefs about why they want to complete a task. Task value includes four subcomponents: intrinsic value, utility value, attainment value, and cost. First, intrinsic value refers to the enjoyment or intrinsic interest in a task, and it is more related to the process of completing a task rather than the results of a task. If individuals place higher intrinsic value in a task, then they tend to be more engaged (Wigfield & Eccles, 2002). This concept is similar to Deci and Ryan's (1985) concept of intrinsic motivation. Second, utility value refers to the usefulness of a task to individuals' current and future goals, and it is related to the outcomes of a task rather than the process. Third, attainment value refers to the importance of doing well on a task and ties in to individuals' self-identity; for example, individuals may place more importance on tasks that confirm key characteristics of their identity. Hence, an individual's conception of the personal importance of a task and the importance of achieving that task to their identity contributes to a task's attainment value (Gaspard et al., 2014). Last, cost refers to the perceived negative aspects of participating in a task. For example, individuals who engage in a task may need to expend energy, resources, and time. By engaging in a particular task, individuals may be giving up the opportunity to perform other tasks. In addition, emotional costs, such as fear and anxiety over a task, may affect individuals. Cost, attainment value, utility value, and intrinsic value work together to form the perceived task value for an individual, and values predict choices such as enrollment in future courses as well as intentions to continue in future courses (Wigfield & Eccles, 2002).

Many factors influence and mediate individuals' expectation for success and task value. According to Eccles and Wigfield's (2002) model, individuals' interpretation of previous task outcomes, affective memories and reactions, and perception of the cultural milieu and other people's thoughts and expectations influence individuals' beliefs about their perceived competence, goals, and identity. When confronted with a task, these beliefs, as well as individuals' perception of the difficulty of a task, affect their expectations for success and subjective task value. Their expectations for success and subjective task value predict achievement behavior, including choice and performance, and over time, their results of their achievement behavior will affect individuals when they form their expectations for success and assign value to future tasks (Wigfield & Cambria, 2010; Wigfield & Eccles, 2002). Interventions have tried to affect both expectations for success and subjective task value, and in this study, one of the main foci is on task value interventions.

Task Value Interventions

Because values have been shown to affect individuals' choices and to relate to achievement performance (Wigfield & Cambria, 2010), interventions have been conducted to try to increase the value students place on academic tasks (e.g., Acee & Weinstein, 2010; Hulleman & Harackiewicz, 2009). In essence, task value interventions encourage students to rethink the personal relevance or to reappraise the value of learning particular content or completing academic tasks. Because this is a relatively new area of research that came about within the last ten years, many researchers use different names to describe these interventions. Some names include value-reappraisal interventions (Acee & Weinstein, 2010), utility value interventions (Durik, Shechter, Noh, Rozek, & Harackiewicz, 2014; Harackiewicz, Canning, Tibbetts, Priniski, & Hyde, 2015; Hulleman, Godes, Hendricks, & Harackiewicz, 2010), or relevance interventions

(Gaspard et al., 2015; Hulleman & Harackiewicz, 2009). In this paper, task value interventions (Harackiewicz & Priniski, 2018) will be used to describe this type of social psychological intervention.

Many task value intervention studies have been conducted within a laboratory with the goal of determining the best methods for helping students reappraise the personal relevance of course tasks. For example, Brown, Smith, Thoman, Allen, and Muragishi (2015) conducted a task value intervention study in a laboratory setting where they asked college students to learn about the usefulness of biomedical research. Students either received a communal (other-oriented) or agentic (self-oriented) message about the value of biomedical research. Brown et al. (2015) found that sharing communal messages, such as how research helps others, increased student motivation to learn biomedical science whereas sharing agentic messages did not. Other task value intervention studies conducted in laboratory settings involved asking college students to learn a new mental mathematics technique for multiplication (Canning & Harackiewicz, 2015; Durik et al., 2014; Hulleman et al., 2010; Shechter, Durik, Miyamoto, & Harackiewicz, 2011). For example, Canning and Harackiewicz (2015) tested to see whether directly telling students about the relevance of the math technique and/or asking students to self-generate ideas about the importance of the new math technique would promote greater interest, perceived utility value, and performance. They found that for students with high confidence, each method and the combination of both methods worked to increase interest, perceived utility value, and performance, but for students with low confidence, the combination of methods (i.e., directly telling them and asking them to self-generate ideas about personal relevance) worked the best. In addition, for students who lacked confidence, directly telling students about the everyday use of the math technique worked better than discussing the potential use of the math technique in future careers. In addition, Durik et al. (2014) tested to see how expectations for success moderated the effects of task value interventions. In Durik et al.'s (2014) research, participants learned the mental math technique and read reasons about the value of the technique. Durik et al. (2014) found that students with high success expectancies for math increased their performance and interest after receiving directly-communicated task value message whereas students with low success expectancies did not benefit from directly-communicated task value messages. To help students with low success expectancies, Durik et al. (2014) gave these students an expectancy boost which told them that based on the results of a pre-test, they had excellent potential to learn the mental math technique. After receiving the expectancy boost, students with low perceived competence performed better than students who did not receive the expectancy boost.

While many studies tested to see which methods were effective for task value interventions in a laboratory setting, Gaspard et al. (2015) tested to see which methods were effective for task value interventions in a classroom setting. In their study, high school students in the intervention group participated in a 90-minute presentation that explained the benefits of learning mathematics and then asked students to determine how mathematics applied to their lives. To do so, students in the text condition made a list describing how mathematics was relevant to their lives while students in the quotations condition read quotations and evaluated which reasons given in the quotations were relevant to them. In addition, students in both groups had homework diaries that they had to fill out twice after the presentation. The first homework diary assignment was to simply recall what they remembered from their original task, and the second homework diary assignment depended on their intervention group; students in the text condition were asked to consider why mathematics was relevant to another person they knew, and students in the quotations condition were asked to explore a website explaining the benefits of mathematics and evaluate which benefits related to them. Gaspard et al. (2015) found that students in the quotations condition had higher utility value, attainment value, and intrinsic value for mathematics than the control group. Students in the text condition had higher utility value than the control group, but no effect was found on attainment value and intrinsic value. When comparing the effects on utility value, the quotations condition had a significantly bigger effect on utility value than the text condition. This study indicates that asking students to evaluate quotations is more effective in task value interventions than asking students to list reasons why mathematics is important. Unfortunately, Gaspard et al. (2015) did not test to see whether these interventions had any effect on the academic achievement of students. Other studies, however, have analyzed whether task value interventions have had positive effects on academic performance.

Many studies have been done to evaluate the effectiveness of task value interventions on raising academic performance of students at the high school or college level. At the high school level, Hulleman and Harackiewicz (2009) asked students in their intervention to write throughout the semester about the relevance of their science courses to their lives. They found that students with low success expectancies who completed the intervention had higher interest in science and had higher course grades than those who did not complete the intervention. No effects were found on students with high success expectancies. At the college level, many studies have been conducted to investigate the effectiveness of task value interventions. For example, Acee and Weinstein (2010) studied the effectiveness of a task value intervention in a college statistics course where students read about the importance of statistics and internalized the message through brainstorming, creating rationales, imagining, and contrasting advantages and disadvantages of learning statistics. They found that students in the task value intervention had significant increases on task value, utility value placed on learning course material, and interest when compared to the control group. In addition, for one of the two classes in which the intervention was administered, students in the intervention group had better performance on a course exam than the control group. Furthermore, Hulleman et al. (2010) and Hulleman, Kosovich, Barron, and Daniel (2016) examined whether task value interventions were effective for students in a college psychology class. For their intervention, students were asked to write an essay about the relevance of psychology to their lives. Both studies found that students who completed task value interventions had better class performance. Last, Harackiewicz et al. (2015) investigated whether task value interventions were effective in introductory biology courses, particularly for first-generation, underrepresented minorities. Students in the intervention group wrote three essays throughout a semester about the relevance of the course material to their lives. Overall, students in the task value intervention group did better on final course grade than students in the control group. Furthermore, the intervention was successful in reducing the achievement gap between first-generation, underrepresented minorities and continuing generation, majority students; the gap in the control group between first-generation, underrepresented minorities and continuing generation, majority students was .84 grade points whereas the gap was only .51 grade points in the intervention group. Harackiewicz et al. (2015) also tested a combination of task value intervention with a values affirmation intervention, which asked students to describe personal values important to them, but they found that those who completed both interventions did not have added benefits beyond than those who only completed the task value intervention. Throughout various studies, task value interventions have been found to have positive effects on course performance at the high school and college level.

Overall, some aspects of task value interventions seem to work better for certain types of students; for example, for students with low confidence, directly receiving messages as well as self-generating messages worked best in promoting utility value and raising performance scores (Canning & Harackiewicz, 2015). In addition, students with low expectations of success benefited from an expectancy boost prior to receiving the intervention (Durik et al., 2014). However, few studies applied these types of findings to interventions conducted in the classroom; many classroom task value studies (Hulleman & Harackiewicz, 2009; Hulleman et al., 2010; Harackiewicz et al., 2015) simply requested students to write about the utility value of the course content in their lives without presenting messages or providing expectancy boosts. Future studies should aim to synthesize many aspects of previously successful task value interventions to develop a research-based task value intervention that could work in introductory mathematics courses. In addition, future studies could also focus on more than just utility value, which is one of the critiques of the task value intervention research.

Critiques of Task Value Intervention Research

Many of the task value interventions focus on asking students to reevaluate the utility value of a course or course material (e.g. Acee & Weinstein, 2010; Harackiewicz et al., 2015; Hulleman & Harackiewicz, 2009; Hulleman et al., 2010). However, task value includes more than just utility value; task value also includes intrinsic value, attainment value, and cost. Many of these intervention studies do not measure intrinsic value, attainment value, and cost, and therefore, they cannot report the effects of task value interventions on other components of task value. Key researchers in the field are bringing attention to this issue. For example, Trautwein et al. (2013) advocate the measurement of all four task value subcomponents (i.e., intrinsic value, attainment value, utility value, and cost) in future research studies. Trautwein et al. (2013) emphasized the importance of this inclusion by suggesting to change the name of the expectancy-value theory to expectancy-values theory. Furthermore, Trautwein et al. (2013) encouraged researchers to look at the interaction effects between value subcomponents in statistical analyses.

While Trautwein et al. (2013) focused on all four task value subcomponents, Barron and Hulleman (2015) emphasized the importance of examining cost in the expectancy-value theory and proposed to reconceptualize and rename this theory to the expectancy-value-cost theory. Barron and Hulleman (2015) pointed to earlier works of Eccles and Wigfield (1995) where cost, defined as task difficulty and perceptions of effort required to successfully complete a task, loaded as separate factors from expectancies and values in a factor analysis. In addition, other research studies supported including cost as a variable in future studies. For example, when Trautwein et al. (2012)

and Lutrell et al. (2010) added intrinsic value, attainment value, utility value, and cost to their measures and when they performed factor analyses, each of the four subcomponents of value loaded onto four different factors. Therefore, because of Eccles and Wigfield's (1995) findings along with Lutrell et al.'s (2010) and Trautwein et al.'s (2012) results, Barron and Hulleman (2015) supported separating cost from the value dimension and using an expectancy-value-cost theory instead. In conclusion, both Barron and Hulleman (2014) and Trautwein et al. (2013) advocate for an inclusion of more measures related to task value, which has not been a focus in previous research studies. To respond to these recommendations, this dissertation study will include additional measures of task value, which will be described in the methods chapter.

Gaps in the Growth Mindset and Task Value Intervention Research

Both growth mindset and task value interventions have strong evidence of success. Many gaps, however, still exist in both the growth mindset and task value intervention research, such as the lack of interventions targeting both expectancy and value and the lack of research conducted in college algebra courses. First, expectancy-value theory is the theoretical framework for task value interventions, yet these task value interventions are only working on the value component of the theory. Although Durik et al. (2014) tied in the expectancy domain by providing expectancy boosts to participants with low expectations for success, no other studies included an intervention to address expectancy alongside task value interventions. This study will investigate whether combining growth mindset interventions, which are conceptually related to expectancy beliefs, and task value interventions will be more effective than task value interventions alone. Currently, growth mindset interventions have been combined with other motivational interventions, including attribution (Good et al., 2003) and sense-of-purpose (Paunesku et al., 2015) interventions. However, a lack of research exists on combining theories of intelligence interventions with task value interventions to see if a positive synergistic effect can be observed. For mathematics in particular, where students tend to complain that they are not math people (Boaler, 2016) and that course material is irrelevant to their lives (Luttrell et al., 2010), a growth mindset intervention paired with a task value intervention seemed reasonable to combine.

Furthermore, there is a lack of research that investigates the effectiveness of growth mindset and task value interventions in college algebra classrooms. Most growth mindset interventions have been conducted in secondary schools (Blackwell et al., 2007; Good et al., 2003; Paunesku et al., 2015; Yeager et al., 2016), and most task value interventions conducted in a college setting have been done in science or social science classrooms (Harackiewicz et al., 2015; Hulleman et al., 2010; Hulleman et al, 2016). Because intelligence beliefs and values perceptions are domain-dependent, more research needs to be done to understand the effectiveness of growth mindset and task value interventions in algebra-based mathematics courses. Interestingly, Shively and Ryan (2013) found that college algebra students who endorsed more fixed mindset beliefs about math intelligence in comparison to their views on general intelligence made lower math course grades. Furthermore, Chouinard and Roy's (2008) research shows that students' utility value and mastery goals in mathematics decline as they advance through high school. When students enter their mathematics course in college, they bring their preconceived notions of mathematics into their college classroom. Task value interventions have successfully improved student perceptions of utility value in statistics

(Acee & Weinstein, 2010) and on math-based tasks (Canning & Harackiewicz, 2015; Durik et al., 2014; Hulleman et al., 2010; Shechter et al., 2011). Therefore, it is possible that conducting growth mindset and task value interventions in algebra-based, college mathematics courses could potentially improve student outcomes. This study seeks to address whether these social psychological interventions are helpful in college mathematics by conducting research in an algebra-based, college mathematics classroom.

Chapter Summary

This chapter first described social cognitive theory as the theoretical framework for this dissertation study. In Bandura's (1986) model of triadic reciprocality, individuals are not driven by internal or external forces; rather, individuals are driven by the interactions of personal, behavioral, and environmental factors. In terms of growth mindset and task value interventions, these interventions serve as environmental factors aiming to influence personal and behavioral factors of students. Specifically, students who hold growth mindset beliefs tend to focus on learning goals (Dweck & Leggett, 1988), attribute their failures to lack of effort (Hong et al., 1999), and seek more academic challenges (Dweck, 1986). Because these goals, attributions, and behaviors are generally desirable in academic settings, researchers have created interventions that aim to increase individuals' beliefs in a growth mindset, and these interventions have been found to be effective in raising the academic performance of certain groups of students (e.g., Aronson et al., 2002; Yeager et al., 2016).

Not only do growth mindset interventions work to improve academic outcomes of certain students, but task value interventions have also been found to do the same. Task values refers to individuals' beliefs about why they want to complete a task, and the subcomponents of task value are intrinsic value, attainment value, utility value, and cost (Wigfield & Eccles, 2002). Task value interventions aim to improve students' perceptions of value when completing a task or taking a course, and they have been found to increase academic performance (e.g., Hulleman et al., 2010; Hulleman et al., 2016). Because both growth mindset and task value interventions have been shown to improve academic outcomes, students taking college algebra could potentially benefit from these interventions, especially because college algebra typically has high failure rates (Herriot, 2006). This dissertation study will examine whether growth mindset, task value, and a combination of growth mindset and task value interventions will benefit students in college algebra in terms of their views on intelligence, self-efficacy, value perceptions, and academic performance. The next chapter will detail the methods of this study.

III. METHODS

The goal of this study was to determine whether certain social psychological interventions can bolster academic performance of students in college algebra. With an experimental, repeated measures design, this study tested the effectiveness of a growth mindset intervention, a task value intervention, and a combination of the two interventions. Because students came from four different sections of college algebra, stratified random assignment to groups was used so that each section would have a proportional amount of students within each intervention group. Students were first stratified according to class section and then randomly assigned to four conditions: growth mindset, task value, combination, and control. Before completing any interventions, students took a pre-survey measuring initial intelligence beliefs, self-efficacy, value perceptions, and demographic information. Later, each participant completed two online activities that were specific to the group to which they were assigned. These activities were spaced about one to two weeks apart. The growth mindset group completed one growth mindset activity and then one control activity, the task value group completed one task value activity and then one control activity, and the control group completed two different control activities. The growth mindset group and the task value group received their interventions during the first round of online activities so that all students in an intervention group would receive treatment at the same time. Because students in the combination group received two interventions, this group was divided further into two groups to counterbalance the order of the interventions; one group completed the task value activity first and then the growth mindset activity whereas the other group completed the growth mindset activity first and then the task value activity. At the end of the study, students took a post-survey measuring final intelligence beliefs, self-efficacy, and value perceptions, and grades were obtained from the instructors.

Research Questions and Hypotheses

The research questions and hypotheses for this study were as follows:

Research Question 1

Do the growth mindset, task value, and combination interventions produce changes in students' intelligence beliefs, self-efficacy, and value perceptions over time from pre-survey to post-survey when compared to the control group?

Hypothesis 1. Students who completed a growth mindset or combination intervention were predicted to have stronger beliefs in the malleability of intelligence from pre-survey to post-survey than students who completed the task value or control intervention. Similarly, students who completed the task value or combination intervention were predicted to value mathematics more and have higher self-efficacy from pre-survey to post-survey than students who completed the growth mindset and control interventions. This hypothesis aligned with previous research results; students who completed a growth mindset activity have had positive changes in their intelligence beliefs (Paunesku et al., 2015), and students who completed a task value activity have had improved value perceptions (Hulleman et al., 2010) and self-efficacy (Hulleman et al., 2016).

Research Question 2

In regard to changes in students' intelligence beliefs, self-efficacy, and value perceptions over time (i.e., from pre-survey to post-survey), do students benefit differently from the growth mindset, task value, and combination interventions based on demographic variables (i.e., gender, race/ethnicity, and first-generation status) and pre-survey measures (i.e., test 1 grades, initial intelligence beliefs, and initial value perceptions) when compared to the control group?

Hypothesis 2. Students of marginalized groups (e.g., minority, first-generation) or students with lower pre-survey scores were hypothesized to have bigger improvements in their intelligence beliefs, self-efficacy, and value perceptions over time if they completed a growth mindset, task value, or combination intervention. This hypothesis aligned with previous research where changes in intelligence beliefs were more likely to be significant for students in marginalized groups (Aronson et al., 2002) and changes in value perceptions were more likely to be significant for students with lower success expectancies (Hulleman & Harackiewicz, 2009).

Research Question 3

Do the growth mindset, task value, and combination interventions have positive effects on final course score when compared to the control group?

Hypothesis 3. Final course scores were expected to be different among intervention groups. Students in the task value or combination group were expected to have higher final course grades than students in the control group. This is because previous task value intervention research has found overall increase in course performance (Harackiewicz et al., 2015; Hulleman et al., 2010). However, for growth mindset interventions, only certain groups, such as low-achieving students, have had positive effects on course performance (Paunesku et al., 2015; Yeager et al., 2016).

Therefore, students who only received the growth mindset intervention were not expected to have overall positive effects on course performance.

Research Question 4

In regard to final course score, do students benefit differently from the growth mindset, task value, and combination interventions based on their demographic variables (i.e., gender, race/ethnicity, and first-generation status) and pre-survey measures (i.e., test 1 grades, initial intelligence beliefs, and initial value perceptions) when compared to the control group?

Hypothesis 4. Students of marginalized groups (e.g. minority, first-generation) or students with lower pre-survey scores were hypothesized to have better course performance if they completed a growth mindset, task value, or combination intervention. Past research has demonstrated that growth mindset and task value interventions increased the academic performance of only certain groups of students. For example, theories of intelligence interventions have specifically helped African-American students (Aronson et al., 2002) and students who have previously failed core courses (Paunesku et al., 2015). In addition, task value interventions have helped first-generation, underrepresented minorities (Harackiewicz et al., 2015) and students who had low success expectancies (Hulleman & Harackiewicz, 2009). Therefore, only students in marginalized groups, such as minority and first-generation students, or students with lower pre-survey scores were predicted to have better course performance outcomes as a result of completing a growth mindset, task value, or combination intervention.

Variables of Interest

For the first and second research questions, the independent variables were intervention group and time, and the dependent variables were student intelligence beliefs and value perceptions. For the third and fourth research questions, the independent variable was the intervention group, and the dependent variables was final course scores. Covariates, including gender, race/ethnicity, first-generation status, course sections, test 1 grades, initial intelligence beliefs, initial self-efficacy, and initial value perceptions, were measured so they could be controlled for during data analyses. In addition, the interactions between the demographic variables, including gender, race/ethnicity, and first-generation status, and the intervention groups were of interest to determine the extent to which some individuals benefit more or less from a particular intervention.

Context of Study

This study was conducted at a large, Southwestern university in four different sections of college algebra, which were arbitrarily labeled as A, B, C, and D. The course sections had different instructors, who had varying grading policies, teaching styles, and exams. In addition, three of the sections met two times a week while one of the sections met three times a week. All the sections were held during different times of the day. Furthermore, the grade distributions of the courses varied in each course section, which is shown in Table 1.

Table 1

Student Enrollment and Grade Distribution of College Algebra Sections

	Course Section			
	A	B	C	D
Students Enrolled in Course	363	378	378	271
Percentage of Students Who Earned an A	9.09%	8.73%	19.05%	28.41%
Percentage of Students Who Earned a B	21.49%	18.78%	25.40%	21.77%
Percentage of Students Who Earned a C	25.34%	20.90%	29.37%	21.03%
Percentage of Students Who Earned a D	16.53%	19.58%	10.05%	14.02%
Percentage of Students Who Earned a F	20.66%	23.28%	12.43%	9.23%
Percentage of Students Who Withdrew from the Course	6.61%	8.20%	3.70%	5.17%
Percentage of Students Who Did Not Complete Course	0.28%	0.53%	0.00%	0.37%

The plurality of students in Course Section A and in Course Section C made a C, the plurality of students in Course Section B made an F, and the plurality of students in Course Section D made an A. Because of the differences between the course sections, course section was controlled for in the data analyses of this study.

Participants

Students who were at least 18 years old were recruited from a large, Southwestern university during the fall of 2016 from four different sections of college algebra, which had a total of 1390 students in the sections. Participants were asked to complete a pre-survey, two intervention activities, and a post-survey; completion of these four study activities were required for study inclusion. Although 1070 students consented to be in the study, only 431 students completed all four required study activities. In addition, course test scores and final grades were required for study inclusion, and 5 students were dropped from the sample because of incomplete course data. Therefore, the final sample consisted of 426 students who finished all study activities and had complete course data.

The sample was 79.1% female, and the participants' ages ranged from 18 to 32 years old (*M*=18.56; *SD*=1.43). In regard to the race/ethnicity of the participants, 40.1% were Hispanic, 39.0% were White, 13.6% were Black, and 7.3% were other races/ethnicities. Furthermore, 82.6% were freshmen, 11.0% were sophomores, 4.9% were juniors, and 1.4% were seniors. Last, 39.9% were first-generation students, and 5.9% of students previously took developmental mathematics.

The university's demographics slightly differed from this study's sample; at the university, 48.1% were White, 34.7% were Hispanic, 10.7% were Black, and 6.6% were other races/ethnicities. Furthermore, 57.9% were females, and 42.1% were male. In the study's sample, there were more females, Hispanics, Blacks, and other races/ethnicities than in the overall university. Many reasons could explain why the sample's demographics differ from the university's demographics. First, it is possible that the demographics of students who take college algebra courses differ from the overall university; college algebra is generally the lowest level of mathematics that can earn post-secondary credit (Herriott & Dunbar, 2009), and it could have a different population than than the overall population of the university. Second, only students who completed all the study's required activities (i.e., taking the pre-survey and post-survey as well as completing two intervention activities) and had complete course data were included in the study's sample. It is possible that the demographics of the students who self-selected into the study by completing all study activities may have been different than the students who were in the course overall. Unfortunately, demographics of students taking college algebra at this university could not be obtained for this study, so the demographics of students in this study could not be compared to the demographics of students who were taking college algebra at the university to determine whether the sample was representative of students taking college algebra.

Procedures

A summary of the timeline and study procedures appears in Table 2. During the fifth or sixth week of the semester, the students took their first course exam, and the researcher obtained the emails of the college algebra students from their instructors. At the beginning of seventh week of the semester, the researcher emailed students about the research study and informed them that the researcher will be coming to the class to explain the study in more detail. During the seventh week, the researcher came to the college algebra class to explain the research project, answered any questions students had about the project, distributed the consent form, and administered the pre-survey (for consenting students) or an alternative assignment (for students who did not consent or who were under 18 years old). By consenting to be in this study, students were consenting to release their assignment and course grades in college algebra as well as their demographic information from university records.

Students who consented to be in the study were asked to complete four study activities: a pre-survey, two online activities (i.e., the intervention or control activities), and a post-survey. Students earned extra credit for completing the four study activities. The amount of extra credit that could be earned by students depended on the preferences of the college algebra instructor; one instructor offered up to 2 extra credit points on the final course score and offered to drop the lowest homework or quiz grade, one instructor offered up to 2.5 extra credit points on the final course score, and two instructors offered up to 10 extra credit points on the final exam. Students who decided not to participate in the study had an opportunity to earn the same amount of extra credit by completing alternative activities. The alternative activities were designed to be relevant to students' college algebra course and take approximately the same amount of time as completing the study activities.

Participants were then randomly assigned to four intervention groups, and they were able to access their set of interventions through an online course management system according to the following timeline; during the ninth or tenth week of the semester, the first intervention became available, and during the 11th or 12th week of the semester, the second intervention became available. Each activity was due one week after initial availability. Participants in each group completed different activities (see Table 3); the growth mindset group completed one growth mindset activity and then one control activity, the task value group completed one task value activity and then one control activity, and the control group completed two different control activities. The combination group was further divided into two random groups to counterbalance the order of the interventions; one group completed the growth mindset activity first and then the task value activity whereas the other group completed the task value activity first and then the growth mindset activity. The order of activities for the growth mindset and task value groups were not counterbalanced so as to give a treatment to all students in an intervention group at the same time as the combination would receive a treatment; therefore, the growth mindset or task value activity were given during the first online activity. Near the end of the semester during the 13th week, the researcher returned to the college algebra classroom to administer the post-survey. After the semester ended, grades of consenting students were obtained from the instructor. Any missing demographic information was obtained from university records.

Table 2

Overview of Study Procedures

Week of Semester	**Activity**
Week 5 & 6	• Students took their first test • Researcher obtained emails of college algebra students from instructor
Week 7	• Researcher informed students of research study and upcoming class visit through email • Researcher attended college algebra class to gain consent and administer pre-survey to students
Week 9 or 10	• Students completed first online intervention or control activity
Week 11 or 12	• Students completed second online intervention or control activity
Week 13	• Researcher attended college algebra class to administer post-survey to students
Week 17	• Researcher obtained student grades from instructors • Research obtained missing demographic information and missing grades from university records

Table 3

Overview of Online Activities for Each Group

	Online Activity	
Group	**1**	**2**
Growth Mindset	Growth Mindset Activity	Control Activity #2
Task Value	Task Value Activity	Control Activity #2
Combination	Growth Mindset Activity	Task Value Activity
Combination (Counterbalanced)	Task Value Activity	Growth Mindset Activity
Control	Control Activity #1	Control Activity #2

Description of the Interventions and Control Conditions

The growth mindset activity required participants to read messages and complete two writing activities (see Appendix A). First, the participants read instructions describing the whole assignment. Yeager et al. (2016) found that indirect framing, where students believed that the interventions were for others, was more effective than direct framing, where students believed that the interventions were for themselves. This finding supports the idea that social psychological interventions should be administered without mentioning specific desirable outcomes for the students themselves as to not make them feel controlled or stigmatized by the interventions (Yeager & Walton, 2011). Therefore, the instructions for the growth mindset activity led the participants to believe that they were reading messages and putting the messages into their own words for the benefit of future college algebra students. The first messages were about how the brain is a muscle and how the brain grows in neural connectivity as a person learns new concepts. These messages were based on messages that Blackwell (2002) used, which were found to be effective in increasing academic performance of students in middle school. The messages, however, were modified to appeal to college students; for example, Blackwell (2002) used examples of how children's brains grow over time, but the growth mindset activity's messages used examples of how adults' brains grow over time. Following these messages about the brain, the participants encountered their first writing activity, which asked them to reflect on a time when they strengthened their neural connections in math. Next, students read messages about the advantages of growth mindsets and the importance of effort and appropriate strategies in learning math. At the end of these messages, students were asked to write a letter to future students summarizing the growth mindset information. Throughout the messages, graphics were included because Blackwell (2002) also included graphics in her messages.

The task value activity (see Appendix B) also used indirect framing. The instructions of the task value activity led the participants to think that their answers would be used to help future college algebra students. During the activity, the participants first read six reasons describing why college algebra could be useful. These reasons focused on the usefulness of college algebra in developing problem solving and critical thinking skills, modeling real-life scenarios, preparing students to learn new quantitative skills in future situations, learning math skills needed in future classes, building positive student habits, and obtaining a college degree. Then, after reading each reason, students rated how much they believed the reason to be true for them personally on a 7-point Likert scale. This activity was inspired by Gaspard et al.'s (2015) activity where students evaluated quotations of perceived usefulness of math, which was found to be effective in raising utility, intrinsic, and attainment value of students.   Third, students wrote a letter to future college algebra students detailing the reasons why learning college algebra is personally relevant to them. This type of prompt, which asked students to describe why something is useful to them, is typically used in task value interventions (e.g., Hulleman et al., 2010; Harackiewicz et al., 2015). Last, participants encountered a writing prompt that asked them to reflect on whether learning college algebra would be beneficial to others, such as their friends, family, community, or society.

For each control activity, students completed ten math problems. The first control activity covered quadratic functions and their applications, and the second control activity covered composition of functions. These topics were chosen based on the suggestions of the college algebra instructors who taught these topics around the same time as when the study activities were administered.

Measures

In this study, Likert-scale items were used to gather data about student intelligence beliefs, self-efficacy, and value perceptions in a pre-survey and a post-survey (see Appendix C). Demographic information was also collected via the pre-survey (see Appendix D). Last, exam grades were collected to measure academic performance.

Measures Related to Self-Theories of Intelligence

This study measured intelligence beliefs, effort beliefs, fixed-trait attributions, and performance avoidance goals. First, intelligence beliefs were measured to determine whether students' intelligence beliefs changed over time. Second, fixed-trait attributions were measured, which is the likelihood of students attributing their failure to the fixed trait of ability. When faced with failure, students with incremental intelligence beliefs tend to attribute their failure to lack of effort whereas students with entity beliefs tend to attribute their failure to fixed ability (Hong et al., 1999). Students who completed a growth mindset intervention may show a decrease in believing that failure was because of fixed ability. Last, performance avoidance goals were measured. Students with entity beliefs of intelligence tend to have goals of hiding one's lack of knowledge (Dweck & Leggett, 1988). Therefore, students who completed a growth mindset intervention may show a decrease in performance avoidance goals.

Intelligence beliefs. To measure perceptions of intelligence, an adaptation of Dweck's (2000) Theories of Intelligence Scale was used; while the Theories of Intelligence Scale asks students to reflect on their general intelligence, the pre-survey and post-survey items used in the current study were slightly modified to ask students to think about their math intelligence in particular. The survey contained three entity theory statements about math intelligence, and students were asked to rate their level of agreement for each statement on a 7-point Likert scale. The three answers were reverse coded and averaged to determine overall perception of intelligence where a "1" indicated a strong belief in the entity theory of intelligence and a "7" indicated a strong belief in the incremental theory of intelligence. Dweck, Chiu, and Hong (1995) conducted reliability tests on this scale, and they found that in six different studies ($N = 69$, $N = 184$, $N = 139$, $N = 121$, $N = 93$, $N = 32$), alpha ranged from 0.94 to 0.98. In the test-retest reliability of the measures over a 2-week interval, Dweck et al. (1995) found the reliability of this scale to be .80 ($N = 62$).

Fixed-trait attributions. To measure whether students attribute failure to fixed traits, Yeager et al.'s (2016) two-item fixed-trait attributions scale was used. Students were presented with the following scenario: "Pretend that, later today or tomorrow, you got a bad grade on a very important math assignment. Honestly, if that happened, how likely would you be to think these thoughts?" Then, students first rated the likelihood of attributing their failure to fixed traits (i.e., "This means I'm not very smart at math.") on a 5-point Likert scale that ranges from "1 Not at all likely" to "5 Extremely likely." The students also rated the likelihood of attributing their failure to lack of appropriate studying techniques (i.e., "I can get a higher score next time if I find a better way to study."). The second item was reverse coded and averaged with the first item to determine a final score. No reliability tests have been done on this measure, but it was selected because other attribution scales, such as the one used in Blackwell et al. (2007), used scenarios that were more appropriate for younger students; however, Yeager et al. (2016) used a scenario to which college students could relate, and Yeager et al. (2016) found a significant change in fixed-trait attributions for students who completed an incremental intelligence intervention. Therefore, the present study also used this scale to test whether growth mindset interventions made a difference in fixed-trait attributions over time.

Performance avoidance goals. The three-item performance avoidance goals subscale from Elliot and Murayama's (2008) Achievement Goal Questionnaire-Revised was used in this study. Students rated how much they agreed with performance avoidance goals on a Likert scale that ranges from "1 Strongly Disagree" to "7 Strongly Agree." These three items were averaged to determine the final score. In a reliability study with 229 undergraduate students in a psychology course, Elliot and Murayama (2008) found the subscale to have a Cronbach's alpha of .83.

Measures Related to Expectancy-Value Theory

Self-efficacy, endogenous utility value, attainment value, and cost were measured in this study. First, self-efficacy is similar to expectation beliefs within expectancy-value theory. Task value interventions have been shown to positively affect self-efficacy (Hulleman et al., 2016), and previous studies have shown differences in the effects of task value interventions on students with high or low self-efficacy (Durik et al., 2014; Hulleman & Harackiewicz, 2009); therefore, self-efficacy was measured in this study. Second, one of the goals of the task value interventions was to increase students' perception of utility value of college algebra, so endogenous utility value, or the perceived usefulness of the skills and knowledge gained in a course for the attainment of future goals (Husman et al., 2004), was measured. Third, attainment value was measured. Trautwein et al. (2013) encouraged the measurement of other subcomponents of value to see if there are any interaction effects between the subcomponents. Because some attainment value and intrinsic value measures have been found to have a high correlation (Gaspard et al., 2014; Trautwein et al., 2013), this study only measured attainment value. Last, effort, emotional, and opportunity cost was measured. Although students may believe that math has high attainment and utility value, cost may be a factor in why the same students have poor academic performance. Few previous research studies have measured and analyzed the role of cost in academic performance (Barron & Hulleman, 2015), so this study will try to address this gap.

Self-efficacy. To measure self-efficacy, items from the self-efficacy subscale of the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich & De Groot, 1990) was used. The original subscale contained nine items. However, "self-efficacy researchers maintain that judgments of self-efficacy depend more heavily on the mastery criteria (i.e., being able to succeed) than on the normative ones (i.e. being better than others)" (Bong & Hocevar, 2002, p. 148). Therefore, three items using normative criteria were dropped. Student responses were recorded on a 7-point Likert-scale that ranged from "1 Strongly Disagree" to "7 Strongly Agree," and scores were averaged to determine a final self-efficacy score. Higher scores reflected higher self-efficacy beliefs whereas lower scores reflected lower self-efficacy beliefs. In Bong and Hocevar's (2002) research, they found that the six-item scale based on mastery criteria had an alpha of .953 when given in a high school algebra class ($N = 358$).

Endogenous utility value. To measure endogenous utility value, or the perceived usefulness of the skills and knowledge gained in a course for the attainment of future goals, Husman et al.'s (2004) endogenous instrumentality scale was used. The scale had four items that asked students to rate the usefulness of learning content or developing knowledge and skills in their math course for their future. Student responses were recorded on a Likert-scale that ranges from "1 Strongly Disagree" to "7 Strongly Agree." One of the items was reversed coded (i.e., I will not use what I learn in my math course), and then all items were averaged for the final score. Higher scores meant that students had higher endogenous utility value. Husman et al. (2004) found the Cronbach's alpha of this scale to be .84 when tested on 207 undergraduates in a human development course.

Attainment value. To measure attainment value, Gaspard et al.'s (2014) attainment value scale was used, which has two subscales: importance of achievement and personal importance. The importance of achievement subscale measured how important doing well in math meant to a person whereas the personal importance subscale measured how personally important math was to a person. The attainment value scale had a total of ten items: four items were about the importance of achievement, and six items were about personal importance. In a study with 1,886 ninth-graders, Gaspard et al. (2014) estimated the scale reliability ρ as an alternative to Cronbach's alpha. They found that their subscales were reliable; importance of achievement had a ρ of .88, and personal importance had a ρ of .83. Student responses were recorded on a Likert-scale that ranged from "1 Strongly Disagree" to "7 Strongly Agree." One of the items was reversed coded (i.e., "To be honest, I don't care about math."), and then the responses were averaged together to determine a final score. A higher score meant that students had higher attainment value.

Cost. To measure cost, Gaspard et al. (2014)'s cost scale was used, which had three subscales: opportunity cost, effort required, and emotional cost. The opportunity cost subscale referred to how much students had to give up in order to do well in math, the effort required subscale referred to how much effort students needed to expend to do well in math, and the emotional costs referred to the extent that negative emotions arose while doing math. The cost scale had a total of 11 items; four items were about opportunity costs, four items were about effort required, and three items were about emotional cost. Gaspard et al. (2014) found that their subscales were reliable; opportunity costs had a ρ of .83, effort required had a ρ of .90, and emotional cost had a ρ of .87. Student responses were recorded on a Likert-scale that ranges from "1 Strongly Disagree" to "7 Strongly Agree," and the responses for each subscale were averaged to determine final scores for each subscale. Higher scores represented higher costs on each subscale.

Demographic Information

On the pre-survey, students self-reported their gender, age, race, ethnicity, and the education level of their parents. Students also answered a question about whether they had taken a developmental math course in the past.

Final Course Score

The numeric final course score measured overall student performance in college algebra. Students' final course grades were obtained from the instructor.

Data Collection

To collect data, the researcher administered an in-class pre-survey and post-survey, which included 39 measures relating to intelligence beliefs and value perceptions. However, demographic information, which consisted of 8 questions, was only collected at pre-survey. Students who did not attend class had an opportunity to take the pre-survey or post-survey via Qualtrics, an online survey tool. The surveys took about 15 minutes to complete. If students had missing survey data, the researcher excluded these students from data analysis. To obtain course grades, the researcher requested the grades of consenting students from the instructors.

Chapter Summary

In this chapter, the methods of the study were described, including the research questions, the participants, the procedures, the description of the intervention and control conditions, the measures, and the data collection process. Overall, this study aimed to determine whether the growth mindset, task value, and combination interventions improved students' intelligence beliefs, self-efficacy, value perceptions, and academic performance over time when compared to the control group. Furthermore, this study also examined whether students benefitted differently from the interventions on the aforementioned outcomes depending on students' demographic variables and pre-survey measures.

To determine whether the interventions were successful, students in the study took a pre-survey, completed two study activities depending on which intervention group they were in, and took the post-survey. Scales about intelligence beliefs, performance avoidance goals, fixed-trait attribution, self-efficacy, endogenous utility value, attainment value, and cost were included on both pre- and post-surveys, but demographic questions were only collected at pre-survey. Grades were obtained from the instructors. In the end, the final sample consisted of 426 students who completed the study and had complete course data. In the next chapter, the data were analyzed to determine the effects of the interventions on intelligence beliefs, self-efficacy, value perceptions, and academic performance.

IV. RESULTS

This chapter describes the results from the preliminary and primary analyses in this study. The preliminary analyses examined the dimensionality, reliability, and the correlations of the pre-survey, verified that no significant differences existed between the intervention groups, and checked to make sure the assumptions of the primary analyses were met. The primary analyses used regression analyses to determine the effects of the interventions on self-report measures and on academic performance.

Preliminary Analyses

The preliminary analyses of this study include participant analyses, factor and reliability analyses, correlational analyses, random assignment verification, and assumption checks. These analyses were run before conducting the primary analyses.

Participant Analyses

The purpose of these analyses is to describe the differences in grade distributions between the students who participated in the study and those who did not. Although 1070 students consented to be in the study, only 1032 students completed the course and received a final grade. Furthermore, only 426 students completed the entire study and had complete course data. Therefore, 606 consenting students finished the course but did not finish the study. The primary analyses only examined the 426 participants who completed the study and had complete course data. To understand the differences between students who did not complete the study and those who did, grade comparisons on final numeric course grade and final letter grade were done between the 426 students who completed the study and the 606 students who did not. For the final numeric course grade, the mean grade for students who completed the study was 78.44 (*SD*=13.43) while the mean grade of students who did not complete the study was 69.73 (*SD*=19.14). When running an ANOVA to compare to the two groups, the ANOVA found that these two groups were significantly different ($F(1,1030)=65.49$, $p<.001$); students who completed the study received higher course grades than those who did not. In terms of letter grade, Table 4 shows the distribution of grades between those who completed the study and those who did not.

Table 4

Distribution of Grades Between Study Completers and Non-Completers

	Completed Study	
	No	Yes
Number of Students	606	426
Percentage of Students Who Earned an A	13.00%	23.70%
Percentage of Students Who Earned a B	21.60%	29.60%
Percentage of Students Who Earned a C	25.70%	25.80%
Percentage of Students Who Earned a D	18.80%	12.70%
Percentage of Students Who Earned a F	20.80%	8.20%

A Chi-square test determined that students who completed the study and those who did significantly differed in letter grades ($X^2(4, N=1032)=53.85$, $p<.001$). Students who completed the study had a higher percentage of students who earned an A or B, and students who did not complete the study had a higher percentage who earned a D or F. The implications of this finding will be discussed in the limitations section in the last chapter of this dissertation.

Exploratory Factor Analysis

To determine the dimensionality of the pre-survey, exploratory factor analyses were conducted in SPSS (version 24.0 for Mac) using principal axis factoring. Oblique rotation was used because the pre-survey measures were hypothesized to correlate with each other (Yanai & Ichikawa, 2007). Because each scale related to either intelligence theory or expectancy-value theory, two separate factor analyses were run. First, a factor analysis for measures related to growth mindset (i.e., intelligence beliefs, fixed-trait attributions, and performance goal avoidance) was run. The Scree plot and Eigenvalues suggested a two-factor solution for these measures instead of the expected three-factor solution; upon inspection of the factor loadings, it was found that the items for fixed-trait attributions crossloaded onto both factors rather than having a factor of their own. This finding was reasonable because fixed-trait attribution was closely related to the intelligence beliefs construct. Once the items for fixed-trait attributions were taken out of the factor analysis, the items for intelligence beliefs and performance avoidance goals separated out into a two-factor solution, as expected. Therefore, the scale for fixed-trait attributions was dropped for the remainder of this study. Second, the pre-survey items related to expectancy-value theory (i.e., self-efficacy, endogenous utility value, attainment value, effort required, opportunity costs, and emotional costs) were placed into a factor analysis. The Scree plots and Eigenvalues suggested a five-factor solution; however, there were many problematic crossloadings in which items loaded on multiple factors. Particularly, some items from the importance of achievement subscale crossloaded on all five factors. The attainment value measure was made up of two subscales: importance of achievement and personal importance. Therefore, because of the crossloadings, the importance of achievement subscale, which had four items, was taken out and only the personal importance subscale, which had six items, was left in the study and was theoretically understood to be a facet of attainment value. Furthermore, the subscales for cost (i.e., effort required, opportunity costs, and emotional costs) loaded onto one factor; therefore, the subscales were collapsed into a single cost scale. In the end, these factor analyses yielded two distinct constructs related to growth mindsets (i.e., intelligence beliefs and performance avoidance goals) and four factors related to expectancy-value theory (i.e., self-efficacy, endogenous utility value, personal importance, and cost).

After having conducted separate factor analyses for scales related to growth mindset and expectancy-value theory and removing problematic items, a factor analysis of all remaining scale items was run to see if they would factor onto six distinct factors when analyzed simultaneously. When the items for cost (C), personal importance (PI), self-efficacy (SE), endogenous utility value (ENUV), intelligence beliefs (IB), and performance avoidance goals (PA) were placed into one factor analysis, the factor analysis successfully factored these scales into a six-factor simple solution, as expected., The eigenvalues for cost, self-efficacy, personal importance, endogenous utility value, intelligence beliefs, and performance avoidance goals were 13.23, 3.86, 2.53, 2.19, 1.82, and 1.24, respectively. The final factor analysis accounted for 70.083% of the variation in the data set, and with 426 subjects and a total of 33 items, or variables, on the survey, the minimum ratio of subjects-to-variables was met for this factor analysis (Bryan & Yarnoud, 1995). Table 5 shows the pattern matrix of the measures used in the primary analysis of this study. Each item had a strong loading on its respective factor, and there were no problematic cross-loadings.

Table 5

Pattern Matrix of Initial Self-Report Measures

	Factor					
Survey Items	C	SE	PI	ENUV	IB	PA
I often feel completely drained after doing math.	**.905**	.058	.026	-.075	-.023	-.046
Doing math is exhausting to me.	**.898**	.057	-.036	-.004	.001	-.020
Learning math exhausts me.	**.894**	.075	-.013	-.061	-.010	-.062
I'd have to sacrifice a lot of free time to be good at math.	**.871**	-.035	.105	.080	.015	.005
I have to give up a lot to do well in math.	**.851**	-.053	.098	.082	.048	.050
Dealing with math drains a lot of my energy.	**.833**	.014	.010	-.008	-.002	.045
When I deal with math, I get annoyed.	**.780**	-.001	-.139	.033	-.007	-.009
Math is a real burden to me.	**.779**	-.052	-.141	-.015	-.022	-.039
I have to give up other activities that I like to be successful at math.	**.775**	-.084	.078	.066	-.007	.010
Doing math makes me really nervous.	**.764**	-.124	.126	-.068	.011	.003
I'd rather not do math because it only worries me.	**.728**	-.048	-.126	-.042	.011	.035
I think I will receive a good grade in this class.	-.002	**.918**	-.049	.020	.002	.025
I am sure I can do an excellent job on the problems and tasks assigned for this class.	-.026	**.834**	-.021	.029	-.040	.028
I expect to do very well in this class.	-.052	**.825**	.032	-.026	.043	-.003
I'm certain I can understand the ideas taught in this course.	-.078	**.820**	.009	.038	.040	-.008
I am certain I can understand the most difficult material presented in this course.	-.007	**.768**	.045	.038	-.069	-.041
My study skills are excellent in this class.	-.037	**.718**	.035	-.096	.026	.000
Math is very important to me personally.	-.009	-.010	**.909**	-.104	.005	-.059
I really care about learning a lot in math.	.067	.050	**.897**	-.086	.014	.070
It is important to me to know a lot of math.	.093	.016	**.817**	.053	-.011	.022
I care a lot about remembering the things we learn in math.	.101	.020	**.776**	.082	.016	.061
To be honest, I don't care about math. (reverse coded)	-.202	-.057	**.702**	.045	-.029	-.056
Math is not meaningful to me. (reverse coded)	-.108	-.008	**.552**	.164	-.017	-.063

Table 5 Continued

What I learn in my math course will be important for my future occupational success.	.072	-.002	.027	**.867**	-.010	.034
I will use the information I learn in my math class in the future.	.111	.073	.077	**.805**	-.023	-.045
I will use the information I learn in my math course in other classes I will take in the future.	-.042	-.022	-.006	**.774**	.015	.026
I will not use what I learn in my math course. (reverse coded)	-.169	-.065	.027	**.662**	.032	-.026
You have a certain amount of math intelligence, and you really can't do much to change it.	-.029	-.012	-.002	.006	**.940**	.011
Your math intelligence is something about you that you can't change very much.	-.021	-.001	.032	-.023	**.877**	-.019
You can learn new things, but you can't really change your math intelligence.	.085	.026	-.039	.028	**.788**	-.003
My goal is to avoid performing poorly compared to others.	-.071	.014	.021	-.048	.004	**.879**
My aim is to avoid doing worse than other students.	.068	-.013	-.017	.054	-.040	**.857**
I am striving to avoid performing worse than others.	-.019	.006	.013	-.007	.024	**.784**

Note. Factor loadings > .40 are in boldface. Cost (C) accounted for 39.222% of the variation, self-efficacy (SE) accounted for 10.714% of the variation, personal importance (PI) accounted for 6.796% of the variation, endogenous utility value (ENUV) accounted for 5.856% of the variation, and intelligence beliefs (IB) accounted for 4.743% of the variation, and performance avoidance goals (PA) accounted for 2.753% of the variation.

Reliability Analysis and Descriptive Statistics

Reliability analyses were run on the six pre-survey measures. Cronbach's alpha (α) was found for each measure to determine internal consistency, and all measures were found to be reliable (α was equal to or greater than .88 for all measures). Each measure had a range from 1-7. The descriptive statistics and the reliability of each measure are presented in Table 6. Each pre-survey measure's mean was slightly above the midpoint of the scale, which indicates that overall, the participants slightly leaned toward growth mindset beliefs, performance avoidance goals, and higher beliefs of endogenous utility value, self-efficacy, personal importance, and cost. Over time, growth mindset beliefs, endogenous utility value, and cost increased while performance avoidance goals, self-efficacy, and personal importance decreased overall.

Table 6

Descriptive Statistics and Reliability of Initial Self-Report Measures

Measure	Number of Items	Pre-Survey *M (SD)*	Post-Survey *M (SD)*	α
Intelligence Beliefs	3	4.92 (1.37)	4.98 (1.46)	.90
Performance Avoidance Goals	3	5.08 (1.39)	4.92 (1.46)	.88
Endogenous Utility Value	4	4.62 (1.34)	4.72 (1.34)	.88
Self-Efficacy	6	4.80 (1.25)	4.50 (1.40)	.93
Personal Importance	6	4.30 (1.34)	4.17 (1.31)	.91
Cost	11	4.11 (1.53)	4.34 (1.50)	.96

Note. All scales ranged from 1-7.

In Table 7, the means and standard deviations of the pre-survey and post-survey measures are reported by group. In the control group, intelligence beliefs, performance avoidance goals, endogenous utility value, self-efficacy, and personal importance decreased while cost increased over time. In the growth mindset group, performance avoidance goals, self-efficacy, and personal importance decreased while intelligence beliefs, endogenous utility value, and cost increased over time. In the task value group, intelligence beliefs, performance avoidance goals, and self-efficacy decreased while endogenous utility value, personal importance, and cost increased over time. In the combination group, performance avoidance goals and self-efficacy decreased while intelligence beliefs, endogenous utility value, and self-efficacy increased over time. To determine whether these changes were statistically significant, regression analyses were run in the primary analyses of this chapter.

Table 7

Means and Standard Deviations for Survey Measures by Group

	Group							
	Control		Growth Mindset		Task Value		Combination	
Measures	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Pre-Survey								
Intelligence Beliefs	5.11	1.33	4.81	1.35	4.81	1.44	4.98	1.35
Performance Avoidance Goals	4.92	1.39	5.14	1.52	5.20	1.32	5.07	1.31
Endogenous Utility Value	4.64	1.19	4.65	1.39	4.60	1.41	4.59	1.36
Self-Efficacy	4.80	1.20	4.90	1.36	4.75	1.23	4.76	1.22
Personal Importance	4.27	1.26	4.34	1.33	4.31	1.45	4.27	1.32
Cost	4.03	1.50	3.98	1.56	4.03	1.54	4.40	1.49
Post Survey								
Intelligence Beliefs	4.93	1.33	5.13	1.52	4.66	1.59	5.22	1.34
Performance Avoidance Goals	4.72	1.44	4.93	1.49	5.05	1.49	4.96	1.42
Endogenous Utility Value	4.49	1.08	4.66	1.41	4.75	1.52	4.98	1.25
Self-Efficacy	4.67	1.11	4.63	1.51	4.24	1.51	4.49	1.40
Personal Importance	3.99	1.13	4.01	1.25	4.33	1.43	4.33	1.37
Cost	4.21	1.47	4.34	1.48	4.36	1.61	4.45	1.43

Correlations

The correlations between the pre-survey measures are found in Table 8. Correlations were run between all pre-survey measures related to intelligence beliefs and value perceptions to explore the relationships between these measures. All the self-report measures besides for the scale measuring the performance avoidance goals intelligence beliefs significantly correlated with each other at the $p < .01$ level. Intelligence beliefs, endogenous utility value, self-efficacy, and personal importance all moderately correlated with each other in the positive direction with the correlations ranging from .28 to .37 with the exception of the strong correlation between endogenous utility value and personal importance ($r = .65$). Cost had a moderate to strong correlation in the negative direction with intelligence beliefs, endogenous utility value, self-efficacy, and personal importance

(r ranged from -.39 to -.63). Last, performance avoidance goals were not significantly related to any measure.

Table 8

Correlations Between Initial Self-Report Measures

Measure	*1*	*2*	*3*	*4*	*5*	*6*
1. Intelligence Beliefs	–					
2. Performance Avoidance Goals	-.06	–				
3. Endogenous Utility Value	.28**	-.01	–			
4. Self-Efficacy	.37**	.01	.30**	–		
5. Personal Importance	.33**	.05	.65**	.35**	–	
6. Cost	-.39**	.06	-.40**	-.63**	-.48**	–

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

Random Assignment

This study used stratified random assignment to groups to place 1070 consenting students into groups; students were first stratified by course section and then assigned to a group. However, only 426 students completed the entire study and had complete course data; at the end of the study, 104 students were in the control group, 105 students were in the growth mindset group, 113 students were in the task value group, and 104 students were in the combination group. To confirm that there was no difference between the intervention and control groups in demographics (i.e., gender, first-generation status, race/ethnicity), academic performance baseline measures (i.e., test 1 scores), and pre-survey self-report measures (i.e., intelligence beliefs, performance avoidance goals, endogenous utility value. self-efficacy, personal importance, and cost), Chi-square tests were used to test for differences with categorical variables and one-way ANOVAs were used to test for differences with continuous variables. No significant differences were found between intervention and control groups on demographics, academic baseline measure, and pre-survey measures; therefore, randomization was effective in this study.

Assumption Checks

Before using regression analyses to answer the study's research questions, the data were checked to see if the assumptions of regression were met. The data were tested to verify a linear relationship between predictors and outcomes, a normal distribution of residuals, no or little multicollinearity, no or little autocorrelation, and homoscedasticity (Mendenhall & Sincich, 2003). First, linear relationships were checked by viewing scatterplots between each predictor and outcome. Second, normality of the residuals was tested by interpreting QQ plots. Third, multicollinearity was checked by analyzing the variance inflation factor and tolerance values, which were within normal range. Fourth, autocorrelation was checked using Durbin-Watson test. Last, homoscedasticity was verified by examining scatterplots of predicted values and their residuals and ensuring that the plots were random. No violations of assumptions were found after running all assumption checks, and no outliers or influential points were found after analyzing Cook's distance.

Primary Analyses

Prior to conducting the primary analyses, I standardized all self-report measures to reduce multicollinearity when I tested for interactions (Aiken & West, 1991). Because instructors used different exams, I also standardized test 1 and final course scores within each course section so that I could compare students' grades from all four sections. For the categorical variables of gender, race/ethnicity, first-generation, and the interventions, I dummy coded them so that I could compare the variables to reference groups, which I chose as male, White, continuing generation, and the control group, respectively. For course section, I chose to use effect coding for this variable because no course section could be easily selected as the reference. Therefore, effect coding would allow each course section in the model to be compared to the grand mean instead of a reference group.

For the primary analyses, separate multiple regression analyses were conducted for each outcome measure of interest. There were two general types of outcome measures: self-report outcomes (i.e., intelligence beliefs, performance avoidance goals, endogenous utility value, personal importance, self-efficacy, and cost) and an academic performance outcome (i.e., final course score). Each multiple regression analysis was comprised of two models. Main effects were tested in the first model and interactions were tested in the second model. The main effects model included the dummy coded intervention variables (i.e., growth mindset, task value, and combination) and covariates (i.e., course section, gender, race/ethnicity, test 1 score, and pre-survey measures) as predictors. This model tested the main effects of each intervention after controlling for the covariates. The interaction model was identical to the main effects but included interactions between the intervention and the covariates. Interactions were tested one at a time to determine their level of significance. If interactions were found to be significant, the interaction model was reported as the final model for the outcome measure. If no interactions were found to be significant, the main effects model was reported as the final model. Finally, I also report effect sizes of significant main effects and interactions. Because I standardized all outcome variables, the regression coefficients for the dummy-coded group variable gives the differences of means between the intervention group and the control group in terms of standard deviations, which is a measure of effect size that aligns with Cohen's *d*.

Self-Report Measures

This study analyzed whether interventions affected intelligence beliefs and value perceptions. For each of these self-report measures, interactions were tested to see if the growth mindset, task value, and combination interventions interacted with demographic variables and their corresponding pre-survey self-report measures.

Intelligence beliefs. In this regression analysis, the dependent measure was post-survey intelligence beliefs, and the predictors tested were the intervention groups, course sections, demographics, test 1 score, various pre-survey measures (i.e., intelligence beliefs, endogenous utility value, self-efficacy, and performance avoidance goals; performance avoidance goals was included in the regression because performance avoidance goals is theoretically related to intelligence beliefs), demographics by intervention interactions, and intelligence beliefs by intervention interactions. The overall regression model was significant (R^2=.401, F(16, 409)=17.087, p<.001) and accounted for 40.1% of the variation. Even after controlling for demographics, course sections, pre-survey scores, and test 1 scores, participants in the growth mindset group (b=.235, SE=.097, p=.035, d=.235) and the combination group (b=.253, SE=.109, p=.023, d=.253) had significantly higher post-survey intelligence beliefs than the control group. This confirmed that the growth mindset and combination interventions worked in changing intelligence beliefs as expected. Self-efficacy and performance avoidance goals also significantly predicted post-survey intelligence beliefs while course sections, demographics, test 1 scores, intelligence beliefs, endogenous utility value, and performance avoidance goals did not. No significant interactions were found.

Table 9

Unstandardized Regression Coefficients for Post-Survey Intelligence Beliefs

	Post-Survey Intelligence Beliefs		
Predictor	*b*	*SE*	*p*
Growth Mindset Group	.235*	.097	.035
Task Value Group	-.062	.111	.568
Combination Group	.253*	.109	.023
Course Section A	.000	.111	.994
Course Section B	-.002	.061	.981
Course Section C	-.062	.067	.426
Female	-.153	.077	.114
Black	.130	.097	.149
Hispanic	-.068	.090	.310
Other Race/Ethnicity	-.027	.067	.809
First Generation	-.094	.113	.259
Test 1	.032	.084	.471
Pre-Survey Self-Efficacy	.132**	.045	.006
Pre-Survey Intelligence Beliefs	.491**	.048	.000
Pre-Survey Endogenous Utility Value	.064	.043	.124
Pre-Survey Performance Avoidance Goals	-.096*	.042	.014
		$R^2 = 0.401$	

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

Figure 1 displays the estimated marginal means of post-survey intelligence beliefs, and it shows that those in the growth mindset group (M_{adj}=.132, *SE*=.078) and combination group (M_{adj}=.149, *SE*=.078) had the highest post-survey intelligence beliefs, as expected.

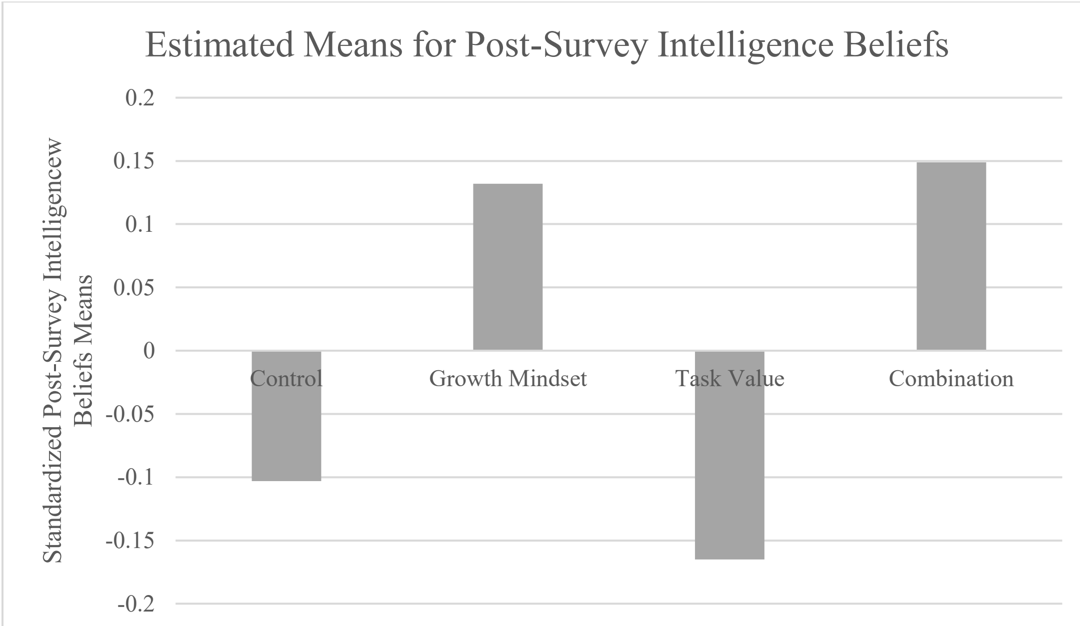


Figure 1. Estimated means for post-survey intelligence beliefs. Students in the growth mindset group (M_{adj}=0.132, *SE*=.078) and the combination group (M_{adj}=0.149, *SE*=.078) had higher post-survey intelligence beliefs means than the control (M_{adj}=-0.103, *SE*=.078). Students in the task value group (M_{adj}= -0.165, *SE*=.075) had lower post-survey intelligence means than the control.

Along with examining estimated means, which is one measure of central tendency, the median of the regression adjusted values (i.e., the values of the response variable for each participant after accounting for the predictors in the regression model) were also examined to see if there were similar effects of the interventions on the median, which is another measure of central tendency. Figure 2 shows the boxplots of the regression adjusted values of post-survey intelligence beliefs for each group. The medians for the growth mindset (*Mdn*=.14, *SD*=.83) and combination (*Mdn*=.25, *SD*=.73) groups were higher than the medians for the control (*Mdn*=-.06, *SD*=.68) and task value (*Mdn*=-.03, *SD*=.86) groups. Therefore, both measures of central tendency (i.e., mean and median) reveal that the growth mindset and combination groups had higher post-survey intelligence beliefs than the task value and control group.

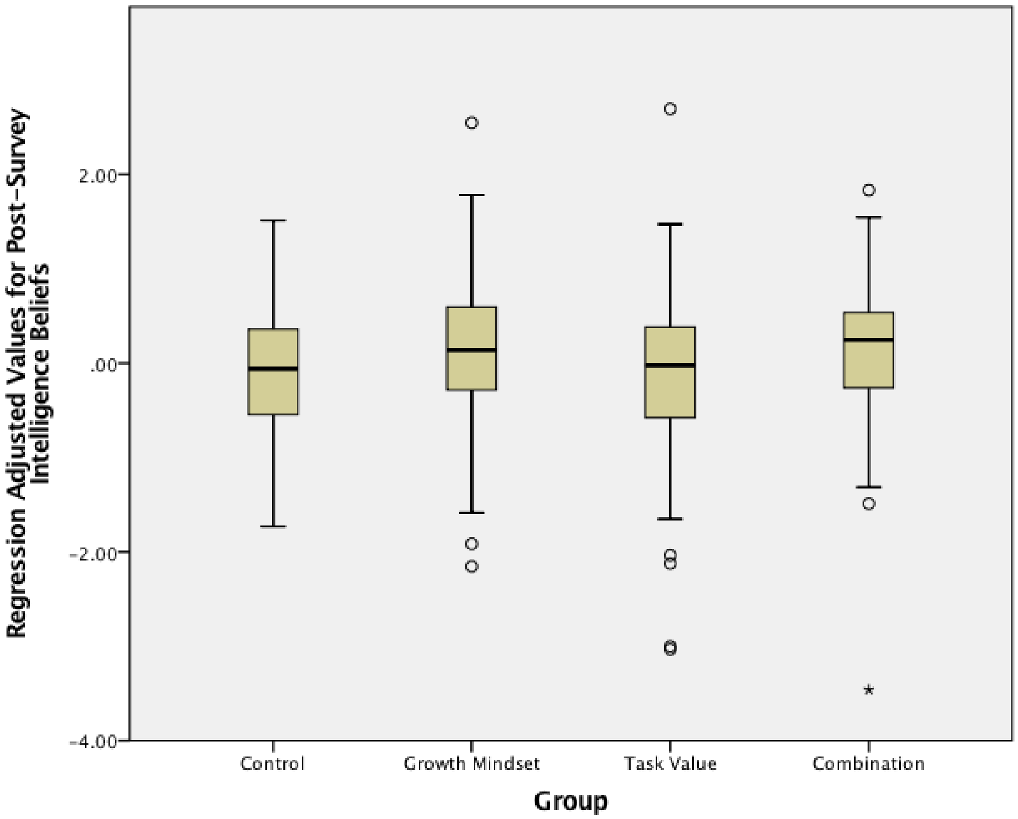


Figure 2. Box plots of regression adjusted values for post-survey intelligence beliefs by group. The circles represent cases that are more than 1.5 times the interquartile range, and the asterisk represents cases that are more than 3 times the interquartile range. The regression adjusted values for the control group had a minimum of -1.73, maximum of 1.51, range of 3.24, interquartile range of .91, median of -.06, and standard deviation of .68. The regression adjusted values of the growth mindset group had a minimum of -2.15, maximum of 2.55, range of 4.70, interquartile range of .92, median of .14, and standard deviation of .83. The regression adjusted values of the task value group had a minimum of -3.03, maximum of 2.70, range of 5.73, interquartile range of .98, median of -.03, and standard deviation of .86. The regression adjusted values of the combination group had a minimum of -3.46, maximum of 1.83, range of 5.30, interquartile range of .81, median of .25, and standard deviation of .73.

Performance avoidance goals (PA). In this regression analysis, the dependent measure was post-survey performance avoidance goals, and the predictors included the intervention groups, instructors, demographics, test 1 score, various pre-survey measures (i.e., intelligence beliefs, endogenous utility value, self-efficacy, and performance avoidance goals), demographics by intervention interactions, and performance avoidance goals by intervention interactions. While the overall regression model was significant (R^2=.390, F(16, 409)=16.320, p<.001) and accounted for 39.0% of the variation, no intervention had an effect on performance avoidance goals. However, identifying as another race/ethnicity other than Caucasian, Black, or Hispanic (*b*=-.260, *SE*=.114, *p*=.023) decreased performance avoidance goals significantly. In addition, higher endogenous utility value (*b*=.097, *SE*=.042, *p*=.021) predicted higher performance avoidance goals, and being in course section C (*b*=.168, *SE*=.078, *p*=.032) increased performance avoidance goals. Variables that did not affect performance avoidance goals include being in course section A or course section B; identifying as Black, Hispanic, female, or first-generation; and initial test 1, self-efficacy, and intelligence beliefs scores.

Table 10

Unstandardized Regression Coefficients for Post-Survey Performance Avoidance Goals

	Post-Survey Performance Avoidance Goals		
Predictor	*b*	*SE*	*P*
Growth Mindset Intervention	.058	.112	.602
Task Value Intervention	.087	.110	.428
Combination Intervention	.078	.112	.488
Course Section A	.035	.062	.574
Course Section B	-.003	.068	.962
Course Section C	.168*	.078	.032
Female	.107	.098	.274
Black	.102	.091	.260
Hispanic	.075	.068	.267
Other Race/Ethnicity	-.260*	.114	.023
First Generation	.114	.084	.178
Test 1	-.033	.045	.473
Pre-Survey Self-Efficacy	-.020	.049	.689
Pre-Survey Intelligence Beliefs	.025	.043	.560
Pre-Survey Endogenous Utility Value	.097*	.042	.021
Pre-Survey Performance Avoidance Goals	.589**	.039	.000
		$R^2 = 0.390$	

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

Endogenous utility value (ENUV). In this regression analysis, the dependent measure was post-survey endogenous utility value, and the predictors tested were the intervention groups, course sections, demographics, test 1 score, and various pre-survey measures (i.e., intelligence beliefs, endogenous utility value, and self-efficacy), demographics by intervention interactions, and endogenous utility value by intervention interactions. The overall regression model was significant (R^2=.545, F(16, 409)=27.125, p<.001) and accounted for 54.5% of the variation. Even after controlling for demographics, course sections, pre-survey scores, and test 1 scores, participants in the task value group (b=.205, SE=.095, p=.031, d=.205) and the combination (b=.387, SE=.097, p<.001, d=.387) group significantly increased their endogenous utility value when compared to the control group. This confirmed that the task value and combination interventions worked in changing endogenous utility value, as expected. In addition, identifying as Black (b=.178, SE=.079, p=.024) or another race/ethnicity other than Black, Hispanic, or White (b=-.212, SE=.099, p=.033) significantly predicted endogenous utility value. Also, higher self-efficacy (b=.100, SE=.042, p=.019) and test 1 (b=.088, SE=.039, p=.026) scores predicted higher endogenous utility value. Variables that did not predict change in endogenous utility value include course sections, gender, first-generation status, being Hispanic, and initial intelligence beliefs.

Table 11

Unstandardized Regression Coefficients for Post-Survey Endogenous Utility Value

	Post-Survey Endogenous Utility Value		
Predictor	*b*	*SE*	*p*
Growth Mindset Intervention	.117	.097	.228
Task Value Intervention	.205*	.095	.031
Combination Intervention	.387**	.097	.000
Course Section A	-.010	.053	.845
Course Section B	.001	.059	.989
Course Section C	.085	.068	.212
Female	-.067	.085	.433
Black	.178*	.079	.024
Hispanic	.028	.059	.642
Other Race/Ethnicity	-.212*	.099	.033
First Generation	.099	.073	.177
Test 1	.088*	.039	.026
Pre-Survey Self-Efficacy	.100*	.042	.019
Pre-Survey Intelligence Beliefs	.028	.038	.457
Pre-Survey Endogenous Utility Value (ENUV)	.522**	.078	.000
Growth Mindset Intervention by ENUV Interaction	.238*	.103	.021
Task Value Intervention by ENUV Interaction	.191	.099	.055
Combination Intervention by ENUV Interaction	.062	.103	.547
	$R^2 = 0.545$		

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

There was also a significant interaction between the growth mindset group and pre-survey endogenous utility value (b=.238, SE=.103, p=.021). To visualize the interaction effect, Figure 3 graphs the regression adjusted values of post-survey endogenous utility value by the pre-survey endogenous utility value for the control and growth mindset groups. The best-fit line for each group was drawn, and the interaction effect can be seen because the slopes of the best-fit lines are different; the best-fit line of the growth mindset group has a steeper slope than the best-fit line of the control group.

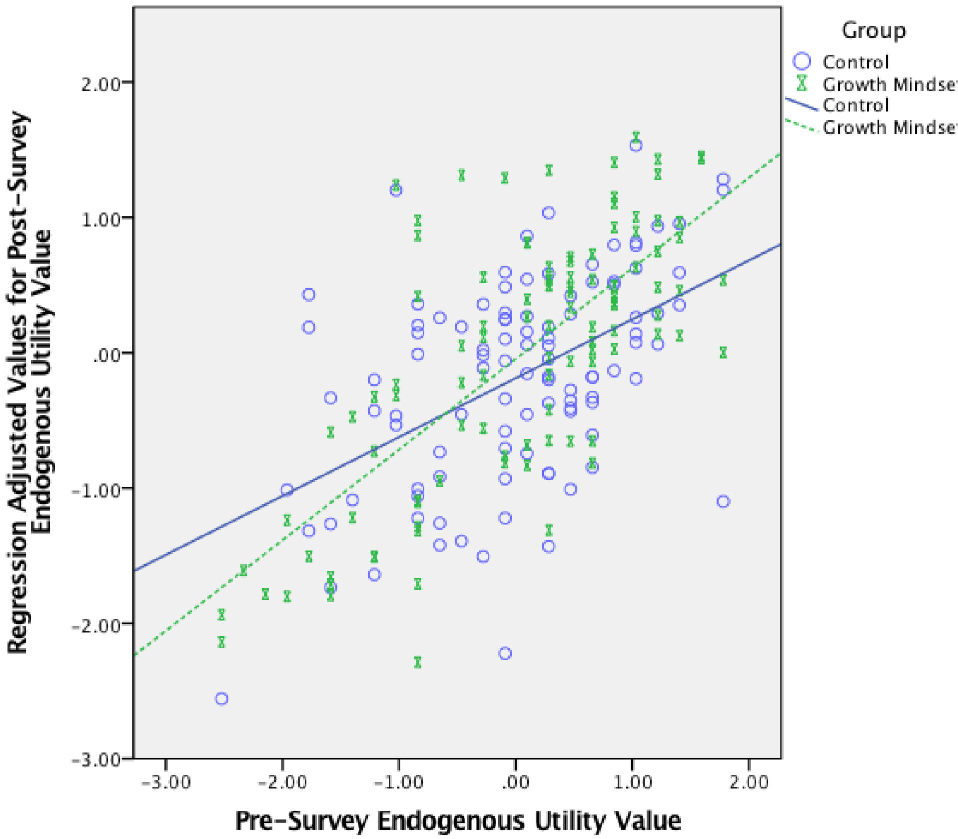


Figure 3. Regression adjusted values for post-survey endogenous utility value by pre-survey endogenous utility value for control and growth mindset groups. A best-fit line for each group was also drawn to show the interaction effect; the slope of the best-fit line for the growth mindset group was different than the slope of the control group.

To further analyze the significant interaction between the growth mindset group and pre-survey endogenous utility value, the estimated means of post-survey endogenous utility value were calculated for students who were one standard deviation below and one standard deviation above the mean of endogenous utility value at pre-survey; these estimated means can be found in Figure 4.

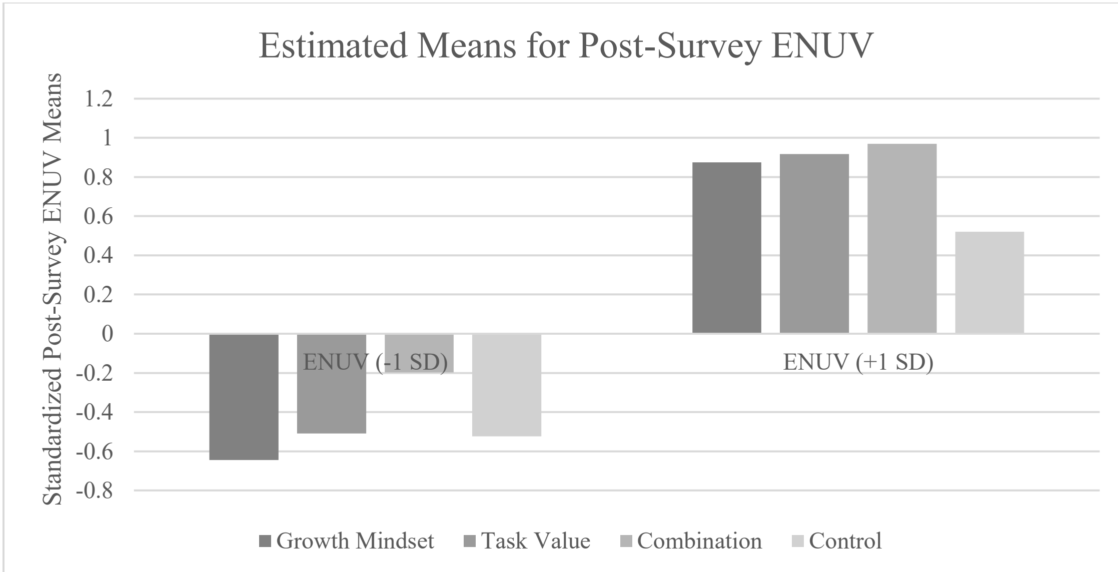


Figure 4. Estimated means for post-survey endogenous utility value (ENUV). The interaction effect being examined is between the growth mindset group and pre-survey ENUV. This graph shows the estimated means for students one standard deviation (SD) below the mean on pre-survey ENUV and for students one SD above the mean on pre-survey ENUV. For students one SD below the mean on ENUV, no group was significantly different than the control on post-survey ENUV. For students one SD above the mean on ENUV, students in the growth mindset group (b=.355, SE=.140, p=.012, d=.355) had significantly higher post-survey ENUV than the control group.

Using Aiken and West's (1991) method to analyze the differences between students one standard deviation below and one standard deviation above the mean of endogenous utility value at pre-survey, it was found that the growth mindset group (b=.355, SE=.140, p=.012, d=.355) was significantly different from the control group on post-survey endogenous utility value for students one standard deviation above the mean; however, for students one standard deviation below the mean, the growth mindset group was not significantly different than the control group on post-survey endogenous utility value. In other words, students who were one standard deviation above the endogenous utility value mean at pre-survey and were in the growth mindset intervention had a significantly higher post-survey endogenous utility value than the control group, but students who were one standard deviation below the endogenous utility value mean at pre-survey and in the growth mindset intervention did not significantly differ from the control group.

Self-efficacy (SE). In this regression analysis, the dependent measure was post-survey self-efficacy and the predictors tested were the intervention groups, course sections, demographics, test 1 score, and various pre-survey measures (i.e., intelligence beliefs, endogenous utility value, and self-efficacy), demographics by intervention interactions, and self-efficacy by intervention interactions. The overall regression model was significant (R^2=.594, F(16, 409)=33.072, p<.001) and accounted for 59.4% of the variation. Even after controlling for demographics, course sections, pre-survey scores, and test 1 scores, participants in the task value group (b=-.272, SE=.089, p=.003, d=-.272) had significantly lower self-efficacy, and being in course section A (b=-.157, SE=.050, p=.002) or course section B (b=-.170, SE=.056, p=.002) or identifying with another race/ethnicity other than Black, Hispanic, or White (b=-.301, SE=.094, p=.001) also decreased self-efficacy. Furthermore, higher test 1 scores (b=.221, SE=.037, p<.001) predicted higher self-efficacy at post-survey. Variables that did not predict change in self-efficacy include being in course section C, being Hispanic or first-generation, and initial intelligence beliefs and endogenous utility value scores.

Table 12

Unstandardized Regression Coefficients for Post-Survey Self-Efficacy

Predictor	Post-Survey Self-Efficacy		
	b	*SE*	*p*
Growth Mindset Intervention	-.044	.092	.632
Task Value Intervention	-.272**	.089	.003
Combination Intervention	-.072	.091	.428
Course Section A	-.157**	.050	.002
Course Section B	-.170**	.056	.002
Course Section C	.109	.064	.091
Female	-.172*	.080	.032
Black	.163*	.074	.029
Hispanic	.081	.056	.148
Other Race/Ethnicity	-.301**	.094	.001
First Generation	-.018	.069	.790
Test 1	.221**	.037	.000
Pre-Survey Self-Efficacy (SE)	.448**	.071	.000
Pre-Survey Intelligence Beliefs	.010	.035	.773
Pre-Survey Endogenous Utility Value	.042	.035	.231
Growth Mindset Intervention by SE Interaction	.165	.090	.068
Task Value Intervention by SE Interaction	.141	.094	.134
Combination Intervention by SE Interaction	.251**	.094	.008
	$R^2 = 0.594$		

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

There was also a significant interaction between the combination group and pre-survey self-efficacy (b=.251, SE=.094, p=.008). To visualize the interaction effect, Figure 5 graphs the regression adjusted values of post-survey self-efficacy by the pre-survey self-efficacy for the control and combination groups. The best-fit line for each group was drawn, and the interaction effect can be seen because the slopes of the best-fit lines are different; the best-fit line of the combination group has a steeper slope than the best-fit line of the control group.

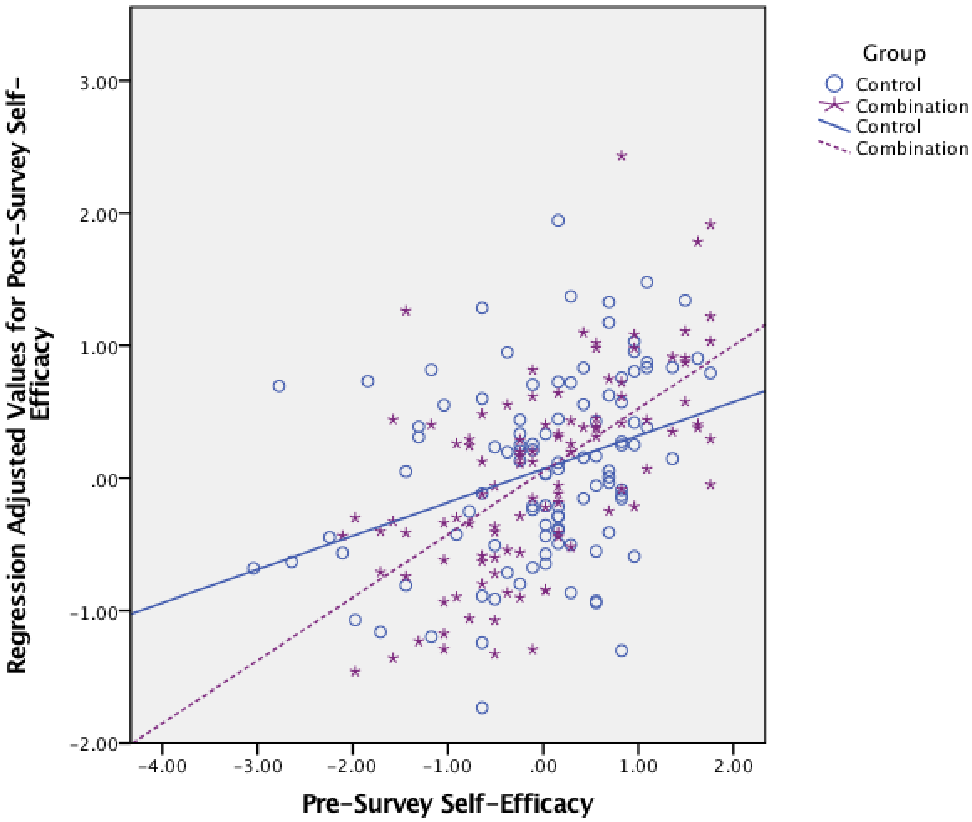


Figure 5. Regression adjusted values for post-survey self-efficacy by pre-survey self-efficacy for control and combination groups. A best-fit line for each group was also drawn to show the interaction effect; the slope of the best-fit line for the combination group was different than the slope of the control group.

To further analyze the combination intervention by pre-survey self-efficacy interaction, the estimated means of post-survey self-efficacy were calculated for students who were one standard deviation below and one standard deviation above the mean of self-efficacy at pre-survey; these means can be found in Figure 6.

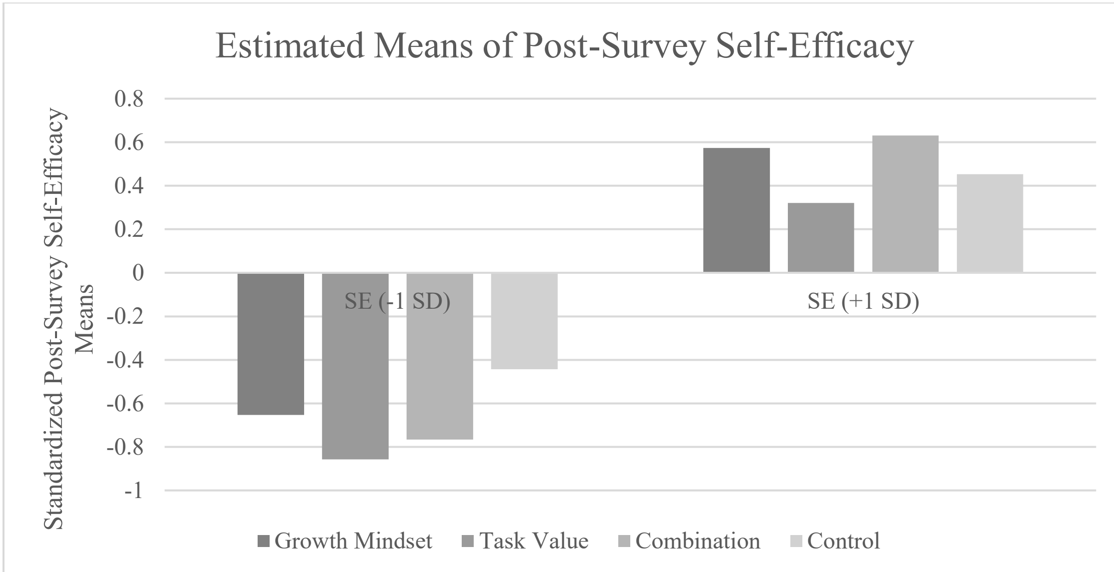


Figure 6. Estimated means for post-survey self-efficacy (SE). The interaction effect being examined is between the combination group and pre-survey SE. This graph shows the estimated means for students one standard deviation (SD) below the mean on pre-survey SE and for students one SD above the mean on pre-survey SE. For students one SD below the mean on SE, students in combination group (*b*=-.323, *SE*=.131, *p*=.014, *d*=.323) were significantly lower on post-survey SE than the control group. For students one SD above the mean on SE, students in the combination group were not significantly different on post-survey SE than the control group.

Using Aiken and West's (1991) method to analyze the differences between students one standard deviation below and one standard deviation above the mean of self-efficacy at pre-survey, it was found that the combination group was significantly different on post-survey self-efficacy from the control group for students one standard deviation below the mean; however, for students one standard deviation above the mean, the combination group was not significantly different on post-survey self-efficacy than the control group. In other words, students who were one standard deviation below the self-efficacy mean at pre-survey and were in the combination intervention had a significantly lower post-survey self-efficacy than the control group (*b*=-.323, *SE*=.131, *p*=.014, *d*=.323), but students who were one standard deviation above the self-efficacy mean at pre-survey and in the combination intervention did not significantly differ from the control group.

Personal importance (PI). In this regression analysis, the dependent measure was post-survey personal importance and the predictors tested were the intervention groups, course sections, demographics, test 1 score, and various pre-survey measures (i.e., intelligence beliefs, endogenous utility value, self-efficacy, and personal importance), demographics by intervention interactions, and personal importance by intervention interactions. Although the overall regression model was significant (R^2=.583, F(16, 409)=29.842, p<.001) and accounted for 58.3% of the variation, no intervention affected personal importance when compared to the control group. Furthermore, course sections, race/ethnicity, first-generation status, and initial Test 1 and intelligence beliefs scores did not predict change in personal importance. However, higher endogenous utility value (b=.139, SE=.043, p=.001) and SE (b=.086, SE=.042, p=.039) predicted higher personal importance.

Table 13

Unstandardized Regression Coefficients for Post-Survey Personal Importance

	Post-Survey Personal Importance		
Predictor	*b*	*SE*	*p*
Growth Mindset Intervention	-.310	.225	.169
Task Value Intervention	-.041	.192	.833
Combination Intervention	-.220	.203	.279
Course Section A	.021	.052	.682
Course Section B	-.085	.057	.132
Course Section C	.075	.065	.255
Female	-.436**	.163	.008
Black	.107	.076	.158
Hispanic	.036	.057	.530
Other Race/Ethnicity	-.156	.095	.101
First Generation	.050	.070	.479
Test 1	.054	.038	.155
Pre-Survey Self-Efficacy	.086*	.042	.039
Pre-Survey Intelligence Beliefs	-.014	.036	.707
Pre-Survey Endogenous Utility Value	.139**	.043	.001
Pre-Survey Personal Importance	.613**	.045	.000
Growth Mindset Intervention by Female Interaction	.375	.247	.130
Task Value Intervention by Female Interaction	.350	.218	.108
Combination Intervention by Female Interaction	.624**	.228	.006
	$R^2 = 0.583$		

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

In addition, a combination intervention by female interaction (*b*=.624, *SE*=.228, *p*=.006) was significant. Figure 7 shows the estimated means of post-survey personal importance for males and females. An interaction effect between the combination intervention and females can be seen; the combination intervention significantly increased personal importance for females but did not increase personal importance for males.

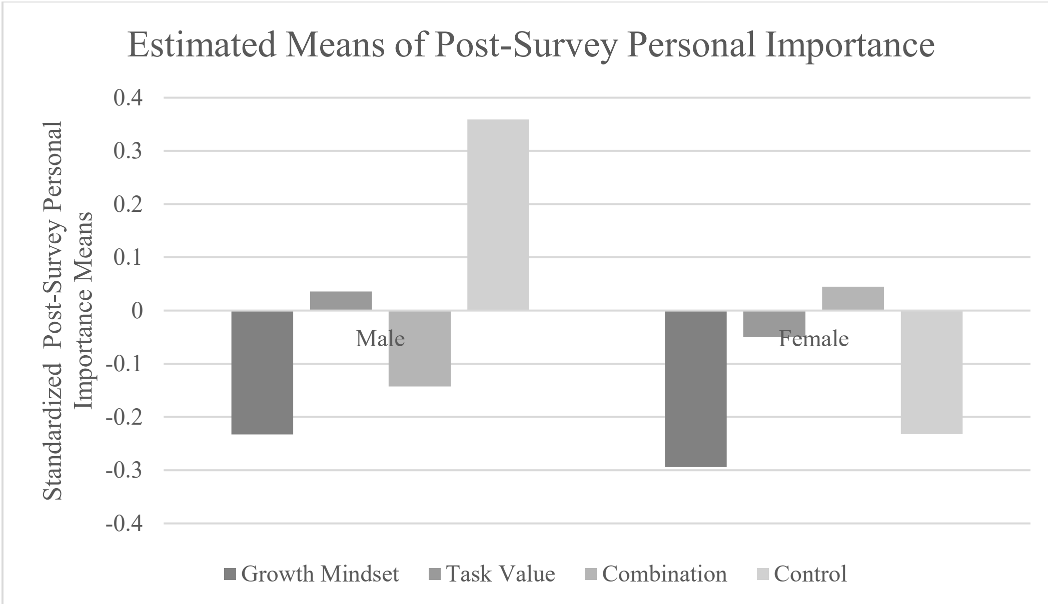


Figure 7. Estimated means for post-survey personal importance for males and females. The interaction effect being examined is between females and the combination group. Females in the combination group had significantly higher post-survey personal importance than females in the control group. However, males in the combination group did not have higher post-survey personal importance than males in the control group.

Along with examining estimated means, the median of the regression adjusted values were also examined to see if there were similar female interaction effects with the combination group. Figure 8 shows the boxplots of the regression adjusted values of post-survey personal importance for all groups by each gender. Similar to the pattern for estimated means, the median for post-survey personal importance for females in the combination group (*Mdn*=.25, *SD*=.73) was higher than the median for females in the control group (*Mdn*=-.25, *SD*=.56); however, the median for males in the combination group (*Mdn*=.08, *SD*=.84) was not higher than the median for males in the control group (*Mdn*=.20, *SD*=.58). Therefore, both measures of central tendency (i.e., mean and median) support that females in the combination group increased in post-survey personal importance when compared to the control group while males in the combination group did not.

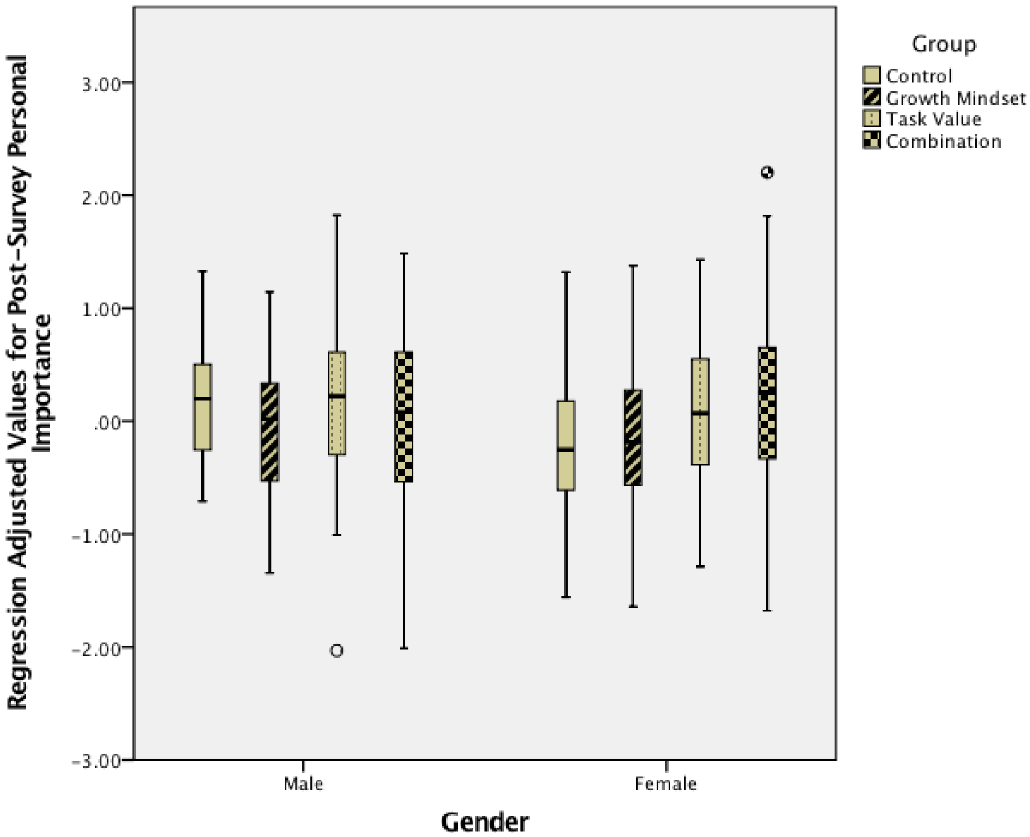


Figure 8. Box plots of regression adjusted values for post-survey personal importance for the four groups by gender. The significant interaction effect was between the combination group and females. For males, the regression adjusted values for the control group had a minimum of -.71, maximum of 1.33, range of 2.04, interquartile range of .89, median of .20, and standard deviation of .58, but the regression adjusted values of the combination group had a minimum of -2.01, maximum of 1.49, range of 3.50, interquartile range of 1.18, median of .08, and standard deviation of .84. For females, the regression adjusted values of the control group had a minimum of -1.56, maximum of 1.32, range of 2.88, interquartile range of .80, median of -.25, and standard deviation of .56, but the regression adjusted values of the combination group had a minimum of -1.68, maximum of 2.20, range of 3.88, interquartile range of 1.04, median of .25, and standard deviation of .73.

Cost. In this regression analysis, the dependent measure was post-survey cost and the predictors tested were the intervention groups, course sections, demographics, test 1 score, and various pre-survey measures (i.e., intelligence beliefs, endogenous utility value, self-efficacy, and cost), demographics by intervention interactions, and cost by intervention interactions. Although the overall regression model was significant (R^2=.668, F(16, 409)=51.459, p<.001) and accounted for 66.8% of the variation, no intervention affected cost when compared to the control group. However, being in course section A (*b*=.179, *SE*=.083, *p*=.382) and being female (*b*=.179, *SE*=.058, *p*=.013) increased cost. In addition, having higher test 1 scores (*b*=-.123, *SE*=.063, *p*<.001) and higher self-efficacy (*b*=-.084, *SE*=.034, *p*<.001) lowered cost. Variables that did not predict change in cost include first-generation status, race/ethnicity, course section B, course section C, and initial intelligence beliefs and endogenous utility value.

Table 14

Unstandardized Regression Coefficients for Post-Survey Cost

	Post-Survey Cost		
Predictor	*b*	*SE*	*p*
Growth Mindset Intervention	.096	.072	.248
Task Value Intervention	.071	.083	.382
Combination Intervention	-.021	.081	.802
Course Section A	.179**	.083	.000
Course Section B	.063	.045	.213
Course Section C	-.059	.050	.307
Female	.179*	.058	.013
Black	-.034	.072	.610
Hispanic	.052	.067	.301
Other Race/Ethnicity	.006	.050	.940
First Generation	.022	.084	.720
Test 1	-.123**	.063	.000
Pre-Survey Self-Efficacy	-.084*	.034	.038
Pre-Survey Intelligence Beliefs	-.009	.040	.775
Pre-Survey Endogenous Utility Value	-.030	.032	.358
Pre-Survey Cost	.671**	.032	.000
	$R^2 = 0.668$		

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

Course Performance Outcome

In this regression analysis, the dependent measure was numeric final course score and the predictors tested were the intervention groups, demographics, test 1 score, and various pre-survey measures (i.e., intelligence beliefs, endogenous utility value, and self-efficacy), demographics by intervention interactions, and all pre-survey measures by intervention interactions. Course sections were not controlled for in this regression because all scores were already standardized for each course section.

Although the overall regression model was significant (R^2=.525, F(16, 409)=38.058, p<.001) and accounted for 52.5% of the variation, no intervention affected final course score. However, the combination intervention (b=-.184, SE=.097, p=.058, d=-.184) was marginally significant; the students in combination group had lower final course scores than the control group. Also, students who identified as Black (b=-.156, SE=.079, p=.048) had lower final course scores while those with higher test 1 scores (b=.582, SE=.039, p<.001) and SE scores (b=.176, SE=.039, p<.001) had higher final course scores. Variables that did not predict final course grade include being female, Hispanic, other race/ethnicity, or first-generation. Initial intelligence beliefs and endogenous utility value also did not predict final course grade. No significant interactions were found.

Table 15

Unstandardized Regression Coefficients for Standardized Final Course Grade

	Final Course Grade		
Predictor	*b*	*SE*	*p*
Growth Mindset Intervention	.040	.098	.685
Task Value Intervention	.028	.095	.765
Combination Intervention	-.184	.097	.058
Female	.139	.085	.103
Black	-.156*	.079	.048
Hispanic	.097	.059	.103
Other Race/Ethnicity	-.053	.100	.593
First Generation	-.131	.074	.077
Test 1	.582**	.039	.000
Pre-Survey Self-Efficacy	.176**	.041	.000
Pre-Survey Intelligence Beliefs	.024	.037	.523
Pre-Survey Endogenous Utility Value	.008	.037	.829
	R^2 = 0.525		

Note. * p < .05. ** p < .01.

Chapter Summary

This chapter detailed the results of the preliminary and primary analyses. In the primary analyses, the dimensionality, reliability, and the correlations of the pre-survey were examined. The exploratory factor analyses revealed that the fixed-trait attribution items and the importance of achievement items crossloaded with other factors, so they were removed from further analyses; therefore, the self-report measures that were analyzed during the primary analyses were intelligence beliefs, performance avoidance goals, endogenous utility value, self-efficacy, personal importance, and cost. The primary analyses used regression analyses to determine the effects of the interventions on self-report measures and on academic performance. Growth mindset interventions positively changed intelligence beliefs, task value interventions increased endogenous utility value and decreased self-efficacy, and combination interventions increased both intelligence beliefs and endogenous utility value. Furthermore, interaction effects were found with endogenous utility value, self-efficacy, and personal importance. First, students who were in the growth mindset group and were one standard deviation above the mean in pre-survey endogenous utility value increased in post-survey endogenous utility value. Second, students who were in the combination group and were one standard deviation below the mean of pre-survey self-efficacy group decreased in post-survey self-efficacy. Third, students who were female and were in the combination intervention group increased in post-survey personal importance. No main or interactive effects were found for performance avoidance goals, cost, or academic performance.

V. DISCUSSION AND CONCLUSION

This chapter explains the effects of the interventions on self-report measures and on final course score. It also includes a discussion of the study's limitations, directions for future research, and implications for instruction.

Effects of Interventions on Self-Report Measures

This study aimed to determine the effects of the interventions on the primary self-report outcomes of intelligence beliefs and endogenous utility value. In addition, the study examined whether the interventions affected outcomes conceptually related to intelligence beliefs (i.e., performance avoidance goals) and endogenous utility value (i.e., personal importance, cost, and self-efficacy). Each finding on the self-report measures is discussed below.

Intelligence Beliefs and Endogenous Utility Value

This study found adds to current literature in various ways. First, one of the main questions of this study asked whether the growth mindset, task value, and combination interventions had effects on intelligence beliefs and value perceptions in college algebra. The study found that the growth mindset intervention positively affected intelligence beliefs, the task value intervention positively affected endogenous utility value, and the combination intervention positively affected both intelligence beliefs and endogenous utility value. These findings corroborate previous studies that show that growth mindset interventions positively affect intelligence beliefs (e.g., Aronson et al, 2002; Blackwell et al, 2007; Paunesku et al., 2015) and task value interventions increase utility value (e.g., Acee & Weinstein, 2010; Hulleman et al., 2010), and they extend the findings to a college algebra classroom. Second, the task value intervention, which asked students to rate reasons why college algebra was useful to them and to write a letter to future students describing college algebra's usefulness, was a novel intervention based on the ideas of interventions previously tested (i.e., Gaspard et al., 2015; Hulleman et al., 2010); this study confirmed that this specific kind of task value intervention worked to increase utility value in college algebra. Last, the combination intervention affected both intelligence beliefs and endogenous utility, which shows that a combination intervention can work to change two unique outcomes. This finding adds to the literature base because it shows that combining growth mindset and task value interventions can result in changes in both intelligence beliefs and endogenous utility value. This had not been previously shown.

It is also worthwhile to note that generally, the growth mindset intervention did not have an effect on endogenous utility value, and the task value intervention did not have an effect on intelligence beliefs; each intervention had discriminant validity and only affected the variables that it intended to change. The one exception to this rule were students who initially had higher endogenous utility value at pre-survey and who completed only the growth mindset intervention; these students also had an increase in endogenous utility value by the end of the study. This was a surprising finding because the growth mindset intervention did not ask for students to reevaluate their values. It is possible that because these students already saw their college algebra course as having more endogenous utility value than the average student, learning about growth mindsets and seeing mathematics as a way to increase mathematics intelligence made the course more valuable to them. More research will need to be conducted in the future to understand this finding further.

Performance Avoidance Goals

In Yeager et al.'s (2016) study, students who received a growth mindset intervention had lower performance avoidance goals at the end of the study, and this study expected to find the same result. However, neither the growth mindset nor the combination interventions in this study produced lower performance avoidance goals. A possible explanation for this finding is the wording of the survey. In Yeager et al.'s (2016) study, the questions pertaining to performance avoidance goals asked students to think about their main goals for the school year. In this study's survey, the scale on performance avoidance goals did not specify for students to reflect on their main goals for the math course; rather, the scale generically asked whether students agreed with a general performance avoidance goal without mentioning their mathematics course. In the future, it is recommended that research use more specific survey items when measuring performance avoidance goals. Previously, Pajares and Miller (1995) discussed the importance of specificity in motivational scales; particularly, they found that self-efficacy scales should be specific in the tasks being assessed and the domain of functioning. Pajares and Miller's (1995) reasoning holds true for performance avoidance goals as well; without specifying students to analyze their main goal in the domain of their mathematics classroom, it is possible that the results from the performance avoidance goals scale are not specific enough to capture the goals of the students. This is further supported by the fact that growth mindsets and performance avoidance goals were not correlated in this study although typically they are found to be negatively correlated (Dweck & Leggett, 1988, Mangels et al., 2006); the lack of specificity in the items about performance avoidance goals may have led to this study not finding any correlations between intelligence beliefs and performance avoidance goals. Future research should include more specific scales on performance avoidance goals to address this issue.

Personal Importance

To determine whether task value interventions affected values other than utility value, this study examined the effect of the interventions on personal importance, which is a subscale of attainment value and measured how important math is to a person. In Gaspard et al. (2015), which tested two different task value interventions, one of their task value interventions (the quotations condition) positively affected attainment value while the other task value intervention (the text condition) did not. In Gaspard et al.'s (2015) study, students in the text condition made a list describing how mathematics was relevant to their lives while students in the quotations condition read quotations and evaluated which reasons given in the quotations were relevant to them. The task value intervention used in this study was a mixture of the two conditions; students read statements about how their mathematics course could be relevant to their lives and rated the extent to which the statements reflected their beliefs. However, instead of asking students to write about which statements were relevant to them, students were then given an open-ended prompt about the usefulness of their college algebra course. It is possible that specifically asking students to evaluate and write about each statement, similar to how Gaspard et al. (2015) conducted their quotations condition, could have resulted in a change in attitude about the personal importance of mathematics. However, this study's intervention allowed students more freedom to write about whatever they see fit, similar to Gaspard et al.'s (2015) text condition. Both this study's task value intervention and Gaspard et al.'s (2015) text condition intervention did not affect attainment value. To gain more clarity on how to increase attainment value, future research can test particular aspects of interventions and compare different conditions to see which ones positively affect attainment value.

Although students did not have an overall change in personal importance, one particular group did have a change; females in the combination group increased in post-survey personal importance whereas males in the same group did not. This result conflicts with other findings in the field. Particularly, Gaspard et al. (2015)'s study examined gender effects on change in intrinsic and attainment value. Their study did not find any gender interactions for attainment value, but they did find gender interactions with intrinsic value; at a post-survey given six weeks later, females in the quotations condition had an increase in intrinsic value whereas males who completed the same intervention did not. For students in the text condition, females and males did not significantly differ in intrinsic value. In a post-survey given five months later, gender interactions were no longer significant for the quotations condition. Gaspard et al.'s (2015) research and this study's findings raise questions about the consistency of gender interactions on change in value. First, Gaspard et al. (2015) did not find significant gender interactions with attainment value although this study found significant gender interactions with personal importance, a subscale of attainment value. Second, Gaspard et al. (2015) found gender interactions on intrinsic value for only one of their two task value interventions. In this study, the task value intervention alone did not interact with gender, but the combination of the task value and growth mindset interventions did. Third, the gender interaction on intrinsic value was found to be no longer significant at a five-month post-survey. This study conducted a post-survey a few weeks after the intervention and did not conduct a follow-up post-survey months later. It is possible that the combination intervention by gender effect on personal importance could fall out if a post-survey were given at a later time. Because of the inconsistent findings in this study when compared to Gaspard et al.'s (2015) study, more research will need to be conducted to clarify the effect of gender on changes in value. Specifically, future research should include both intrinsic value and attainment value in their measures, test a variety of task value and growth mindset interventions in isolation and in combination, and give a post-survey months after students complete the intervention to determine whether gender interactions and changes in value persist over time.

Cost

Barron and Hulleman (2014) noted how cost was not included as a measure in most intervention studies within expectancy-value theory, and this study aimed to address this issue by including a measure on cost, which covered emotional costs, opportunity costs, and effort required. This study found cost was not affected by any of the interventions. It was possible that students in the growth mindset or task value intervention could have perceived their math course to be more costly; after finding more value in mathematics and/or after believing that mathematics intelligence was malleable, students could potentially become more invested in the course and believe that their math course required more effort, produced more emotional burden, or caused them to give up more time to succeed in the course. However, it is good to note that cost did not increase for students who received interventions. This finding contributes to the literature by revealing that growth mindset and task value interventions neither increase nor decrease cost for students; growth mindset and task value interventions, which changed intelligence beliefs and endogenous utility value, respectively, did not increase burden on effort, emotions, or opportunities.

Self-Efficacy

One of the most surprising findings of the study was that students who only completed the task value intervention had significantly lower self-efficacy by the end of the study. Furthermore, students who initially had lower self-efficacy and completed both the growth mindset and task value intervention also had significantly lower self-efficacy. These results are surprising because Hulleman et al. (2016) found that the task value interventions in their study increased success expectancies. Hulleman et al.'s (2016) explained the increase in success expectancies by suggesting that "people like what they are good at and do better at what they like" (p. 13). They posited that because students valued and liked what they were learning, they in turn did better in the course. In this study, however, this logic did not hold. Although students valued the course content more, this did not translate to more confidence in the course. This study could have found different results because of the different contexts of the study; Hulleman et al.'s (2016) study was conducted in an introductory psychology college course while this study was conducted in a college algebra course. It is possible that although Hulleman et al.'s (2016) findings were true for psychology courses, which are social science courses, the same may not be true for math courses. In fact, when task value interventions were done in a laboratory setting using math skills, studies have found varying effects of task value interventions on self-efficacy.

Most published task value interventions have not been done in a math course, but other studies have tested task value interventions with math skills; Durik et al. (2014) and

Canning and Harackiewicz (2015) examined the effectiveness of task value interventions when learning a mental math technique. Findings from both of these studies can help explain the effects of this study's interventions on self-efficacy. First, Canning and Harackiewicz's (2015) research found that for students with low confidence, reading examples of why a mental math technique was useful in everyday leisure activities increased perceived competence when compared to reading examples of why the mental math technique was useful in both future careers and everyday leisure activities. However, for students with high confidence, the opposite was true; reading examples of why the mental math technique was useful in both future careers and everyday leisure activities significantly increased perceived competence when compared to reading examples related only to everyday leisure activities. These findings indicate that receiving different sets of examples can have different effects on perceived competence. Canning and Harackiewicz (2015) concluded that for students with low confidence, examples about future careers could have threatened their competence because they could not envision themselves using the mental math technique in their future career. Following this reasoning, it is possible that the unique set of examples in this dissertation study hurt students' self-efficacy, particularly because of the different types of examples given. Students with high confidence in Canning and Harackiewicz's (2015) study benefitted from receiving examples from two areas of life. In this dissertation study, students in the task value group received examples of how their college algebra course was useful in six different ways (i.e., developing problem solving and critical thinking skills, modeling real-life scenarios, preparing students to learn new quantitative skills in future situations, learning math skills needed in future classes, building positive student habits, and obtaining a college degree). These reasons included examples related to everyday life and future careers as well as many other areas of life. It is possible that the diversity of these reasons had an overall negative effect on students' self-efficacy; too many examples from varying areas of life may have overwhelmed the students because they could relate to some examples but not others.

While Canning and Harackiewicz's (2015) study gives insight into why students in the task value group may have decreased in self-efficacy, Durik et al.'s (2014) research is useful to understand why only students who initially had lower self-efficacy in the combination group significantly decreased in self-efficacy. In Durik et al.'s (2014) study, those with low self-efficacy benefited from a message that they termed "an expectancy boost"; this message, which participants read before the intervention, led the participants to believe that they were expected to do well on the mental math technique that they were about to learn. In this study, it is possible that for those students who completed the combination interventions, the growth mindset intervention served as an "expectancy boost" and protected students from a drop in self-efficacy due to the task value intervention by showing that that it is possible to improve in math with effort. However, for students with the lower self-efficacy from the beginning, the growth mindset did not protect them, implying that they needed more of an expectancy boost than the growth mindset intervention gave them. Those in the task value group, who did not receive any kind of expectancy boost, uniformly had lower self-efficacy than the control group regardless of their initial self-efficacy beliefs. In the future, when task value interventions are conducted in math courses, it may be worthwhile to include an expectancy boost to protect against a drop in self-efficacy as the course goes on. As few task value interventions have been done in math courses, more studies will need to be done to replicate and confirm these findings.

Effects of Interventions on Academic Performance

In this study, no intervention significantly affected academic performance. Even when testing to see if the interventions had a differential effect depending on demographic variables and pre-survey measures, no effect on final course grades were found. This result was surprising as both growth mindset interventions (e.g., Aronson et al., 2002; Paunesku et al., 2015) and task value interventions (e.g., Hulleman et al., 2016; Canning & Harackiewicz, 2018) have been found to positively affect grades in the past. Some studies did not find an overall effect on academic performance, but they still found a grade increase for certain groups of students, such as low-performers (Hulleman et al., 2016; Paunesku et al., 2015) and African American students (Aronson et al., 2002). Unfortunately, this study did not find an overall positive effect on grades for any group of students with either of the interventions. This finding may have various explanations, so two reasons will be discussed: the academic performance measures used and the context of the study. First, although some studies used overall course grade as the measure for academic performance (Canning & Harackiewicz, 2018; Harackiewicz et al., 2015), others used post-intervention exam scores (Acee & Weinstein, 2010) or final exam scores (Hulleman et al., 2010; Hulleman et al., 2016). This study was run in four sections of college algebra with four different instructors, and in one section, the final exam was optional. Within this section, more than half of the students who completed the study chose not to take the final exam. Of the students who took the final exams, it is difficult to ascertain their level of seriousness when approaching the final exam; because the final exam was optional, it is possible that some students did not take the exam seriously because they knew the exam could potentially not affect their final grade. This possibility calls into question the reliability of the final exam as a measure of final academic performance for an entire section; therefore, final course grade was chosen as the academic performance measure over final exam grade. It is possible that the interventions may have affected final exam grade and not final course grade, but because of the exam policies of the algebra courses, final exam grades were not analyzed in this study.

The second possible explanation for finding no effect on grades relates to the context of the study. Yeager and Walton (2011) shared that the effectiveness of social psychological interventions can be context-dependent, and in the case of this study, the college algebra courses in which these interventions were tested may be the reason why grades were not affected. At the college level, growth mindset interventions increased the overall GPA of African Americans students (Aronson et al., 2002), and task value intervention studies found positive effects on grades in biology (Harackiewicz et al., 2015), psychology (Hulleman et al., 2016), and statistics (Acee & Weinstein, 2010). It is possible that growth mindset or task value interventions may improve overall college GPA or grades in particular Science, Technology, Engineering, and Math (STEM) courses, but for algebra-based mathematics courses, other types of intervention may be needed alongside social psychological interventions, which only aim to change the perception of students.

The growth mindset and task value interventions improved intelligence beliefs and endogenous utility value, respectively, so the interventions changed the intended self-report measures. However, perhaps these are not the ones crucial to increase academic performance in this particular algebra-based mathematics course. This understanding is strengthened by the fact that the combination intervention actually had a marginally negative effect on course grades; students who completed both the growth mindset and task value intervention had lower grades than the control group, although this effect was marginally significant. Other interventions that combined social psychological interventions (Good et al., 2003; Harackiewicz et al., 2015; Paunesku et al., 2015; see Chapter 2 for more details) did not find additional benefits to completing two different social psychological interventions; however, none of these studies found any harm in completing two interventions. Perhaps in college algebra, too many social psychological interventions in one semester could negatively affect students; with new ideas about how math intelligence can grow and how math is personally relevant, yet without other concrete strategies to improve grades, students may falter with their newfound perceptions of math. In a study conducted on perceived interferences in developmental algebra-based mathematics courses, students listed various strategic learning problems, such as self-regulation, stress/anxiety, study methods and learning strategies, and time management, as barriers to course success (Acee et al., 2017). Beyond changing the perception of students about mathematics, it may be beneficial to pair social psychological interventions with interventions where students learn about how to implement strategic learning strategies, such as study methods and time management skills, into their algebra-based math course. For example, Yeager et al. (2016) made a point that working harder with ineffective strategies is not helpful in improving intelligence; rather, students need to use effective strategies or ask for expert advice on strategic learning. Perhaps in a college algebra course, a growth mindset intervention paired with a strategic learning intervention would be more beneficial than two social psychological interventions together. Future research can examine this possibility further.

Limitations

Several limitations exist in this study. First, although the study originally intended to analyze the effects of the interventions on final exam grade, one of the instructors made the final exam optional. This policy called into question the reliability of the final exam as a measure of final academic performance for all students. Without final exam grades, the only academic performance outcome in this study was final course grade. The results showed that these interventions did not affect final course grade, and although it was possible that these interventions affected final exam grades, the limitations of this study did not allow final exam grades to be analyzed.

Second, students did not earn course credit for participating in the study; rather, they only earned extra credit, which was a limitation. Previous research has found that higher-achieving students are more likely to complete extra credit than lower-achieving students (Harrison, Meister, & LeFevre, 2011; Silva & Gross, 2004). Although 1070 students consented to be in this study, only 426 completed all four study activities and received extra credit for participation. This study did have a robust sample size and variation in demographics as well as baseline measures, but because participation was only offered as extra credit, certain types of student who may have had stronger motivation and higher grades completed the study. In fact, when comparing the grades of the study completers with the non-completers, it was found that study completers had higher mean grades and had higher percentages of students who made A’s and B’s within the course. Because growth mindset and task value interventions have been shown to raise academic achievement for students who struggle in their courses, it is important to design study conditions that would encourage lower-achieving students to participate in the interventions. In this study, the instructors did not allow the interventions to be a required portion of their courses, but in the future, these interventions could be incorporated into courses as graded class assignments to encourage more students to complete the study.

Third, this research study relied on self-report data for many outcomes, which may be biased. It is possible that students who received interventions simply answered the post-survey based on what students thought the researcher wanted to hear instead of how students actually felt. Without performance measures to verify self-report data, it is difficult to check that the self-report measures accurately reflected students’ thoughts and behaviors. There have been a few studies that include performance measures to examine students’ actions after receiving interventions. For example, having a growth mindset can lead students to seek more challenging academic work (Blackwell et al., 2007). In Yeager et al.’s (2016) study, rather than simply asking students about their challenge-seeking behavior, Yeager et al. (2016) asked students to assemble a math worksheet and rated the amount of challenging problems students placed on the math worksheet (Yeager et al., 2016). In task value intervention research, Acee and Weinstein (2010) had a performance measure to determine whether their task value intervention increased interest; in their study, students were given the option to click on a link to access a website related to their course material, and whether students clicked the link or not informed the researchers about students' level of interest. Unfortunately, unlike the studies of Yeager et al. (2016) and Acee and Weinstein (2010), this study would have needed students to complete at least two performance measures to verify intelligence beliefs and endogenous utility value self-report measures. Because students already had to complete four study activities to be in the study, which was offered as extra credit, performance measures were not added as to not increase the number of activities that students had to complete in order to be in the study. Future research, however, may want to explore further how to use performance measures to verify measures of intelligence beliefs and endogenous utility value.

Directions for Future Research

In this study, the growth mindset and task value interventions positively affected intelligence beliefs and endogenous utility value, respectively. Although these interventions changed their target psychological outcome, they did not affect academic performance, which other studies have found to be positively affected in the past (e.g., Aronson et al., 2002; Harackiewicz et al., 2015). As this study is one of the first to be conducted in college algebra, it is important to replicate and extend this study to be able to more broadly generalize the effects of growth mindset and task value interventions in college algebra courses. To replicate and extend this study, future research can look into different ways to collect data, to analyze data, and to expand the types of interventions tested to see if these ways could affect academic performance. First, this study can be replicated but designed to collect more academic performance measures. It is possible that the effect on academics can be seen in performance measures closer to when the intervention occurred rather than on final course grade. For example, these interventions could potentially affect a course exam grade that students took shortly after the interventions were given. It would be worthwhile to collect other academic performance measures, such as course exam grades and quiz grades, to analyze in the future. Second, future studies can also include mediation analyses to see if grades could be indirectly affected by interventions. While this study looked at moderating variables through interactions, it did not test for indirect effects of the interventions. Other studies have looked at whether interventions have effects on academic outcomes depending on mediating variables, such as success expectancies (Hulleman et al., 2016) and utility value (Hulleman et al, 2010), and future research can do the same. Third, future studies can investigate a social psychological intervention paired with a study skills intervention. It is possible that for algebra-based courses, students need more than a psychological change; students may also need to learn skills to support their newfound change in perception. For example, a study could examine if a social psychological intervention, where students could learn about the growth mindset and the importance of effort, paired with a study skills intervention, where students could learn about time management and effective study strategies to maximize their time and effort, could be more beneficial.

Implications for Instruction

Research on social psychological interventions in college algebra is in its infancy, and more research would need to be conducted to confirm and extend the findings of this study. However, this study does have some implications for instructors. In college algebra, instructors may want to include social psychological interventions within their courses, particularly growth mindset interventions. Students who did not receive a growth mindset intervention believed less in the idea that math intelligence can grow while students who received a growth mindset intervention believed more in the idea that math intelligence can grow. By including a growth mindset intervention in the college algebra classroom, instructors can increase growth mindset beliefs among their students.

The growth mindset interventions were administered online and took about 40 minutes to complete. College algebra instructors can easily ask students to complete the growth mindset interventions as part of their course requirements without much burden to the instructor; the instructor can place the interventions online (see Appendix A for the intervention) and ask students to complete them as a course assignment. If desired, instructors can further reinforce the growth mindset message by reminding students during class about the importance of effort in building math intelligence, particularly around exam times when encouraging students to put effort into studying. Instructors can also connect attending office hours and visiting tutoring labs as ways of putting in effort in the course.

It is important to note that if instructors want the growth mindset interventions to affect students' final course grade, more would need to be done than simply asking students to complete the online intervention. One of the main messages of the growth mindset interventions is that math intelligence can grow with effort. To encourage students to expend their effort in a useful way, a follow-up intervention or lesson that teaches students effective study strategies for college algebra might be useful. This intervention or lesson can cover topics such as time management, notetaking, or studying for math courses. With a change in perception because of the growth mindsets intervention and an increase in knowledge about study strategies because of the follow-up intervention, it is possible that this combination of interventions can help increase student academic performance.

Last, instructors are recommended to implement growth mindset interventions but to hold off in using this study's task value intervention; the task value intervention decreased self-efficacy and the combination intervention had a marginally negative effect on final course grade. Therefore, until more research is done to determine why task value and combination interventions had negative effects on college algebra students, instructors should consider only administering the growth mindset interventions.

Conclusion

This study tested growth mindset, task value, and combination interventions in college algebra courses, and it found that growth mindset interventions positively affected intelligence beliefs and task value interventions increased endogenous utility value for students in college algebra. Furthermore, the combination of combination interventions was effective in raising both intelligence beliefs and endogenous utility value. This adds to the literature by showing that these particular social psychological interventions work in a college algebra setting, and a combination intervention can work to increase both intelligence beliefs and endogenous utility value. Although these interventions changed their targeted psychological outcome, they did not increase academic performance as measured by final course grade. With high failure rates in college algebra (Herriott, 2006), it is important to continue intervention research in college algebra courses, and this particular study can be replicated and extended to figure out ways to increase academic performance by collecting additional performance measures, using mediational analyses, and examining different combinations of interventions.

APPENDIX SECTION

A. GROWTH MINDSET INTERVENTIONS..109

B. TASK VALUE INTERVENTION 113

C. ITEMS INCLUDED ON PRE-SURVEY AND POST-SURVEY 117

D. DEMOGRAPHICS QUESTIONS FOR PRE-SURVEY 119

APPENDIX A: GROWTH MINDSET INTERVENTION

Instructions: *Thank you for your participation in this extra credit opportunity. To receive extra credit, the entire assignment must be fully completed. In this assignment, which will take about 40 minutes to complete, you will read scientific information about the human brain and learn about intelligence beliefs. We would like to share this information with future college algebra students, but we want your help to explain this information in a more personal way so that future students will better understand the material.*

For the first part of the assignment, you will be asked to read material and then write a reflection on your own life. For the second part, you will read material and write a letter to future students which summarizes the reading in your own words.

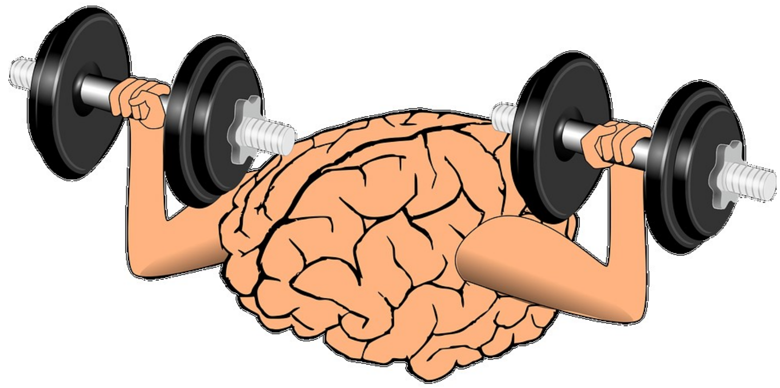
The Brain is a Muscle

Many people believe that humans are born with a certain amount of math intelligence; people are either good or bad at math, which is how they will stay throughout their lives. New research, however, shows that the brain is like a muscle; it gets stronger when people put in the time and effort to complete the right exercises.

Think about how people strengthen their muscles in their arms. They can choose to do push-ups on a regular basis or start lifting weights. If they keep up with a routine consistently, they will be able to do more push-ups or lift a heavier amount of weights as time goes by.

The human brain works in a similar way. Brains are made up of billions of nerve cells called neurons, and neurons connect and communicate with each other. As people learn more and consistently practice and review what they have learned, the connections between the neurons strengthen. It is the connections between the neurons that help people think and solve problems.

Neuron connections can be strengthened, but neuron connections can also break. When students fail to reinforce connections through practice and review, neural connections can break. This is similar to how muscles in the arm will be weakened if push-ups and weightlifting aren't done on a regular basis. The ability of the human brain to make and break neural connections is called neuroplasticity.



[Image from https://pixabay.com/en/brain-growth-learning-mindset-1295128/]

The Brain Grows

Scientists first studied the brain of animals to see if they could grow. They placed animals alone in bare cages and compared them to animals that had toys and other animal companions in their cages. The animals that were alone typically ate and slept the majority of the time while the animals who had company played with each other and with the toys. These scientists found that the animals that had company had bigger brains and more connections in their brains than the animals that lived alone. When the animals were presented with new tasks to learn, the animals that had company were also better at completing the tasks. These results were true for even animals that were old; when old animals were given an opportunity to play with other animals and with toys, their brains grew as well.

Scientists also have studied changes in the human brain, which they could see using brain scans. In one study, scientists wanted to know whether brains would change after learning the skill of juggling. Some people were taught to juggle while others were not. After three months, scientists found that those who learned how to juggle had increased gray matter in the area of the brain that sensed motion and anticipated where objects would be in space. Those who did not learn how to juggle, however, did not have an increase in gray matter in their brains.

Not only have scientists found changes in the brain when people learn physical skills, but they have also documented change in the brain when people practice mental skills. For example, students who attended a three-month course focused on working through reasoning problems had increased connectivity in the area of the brain that supported reasoning whereas students who did not attend the course did not have increased connectivity in their brains.

Consider what this means for students' brain when they are practicing problems in math. Each time students learn new concepts and practice problems, their brain is slowly changing and growing stronger.

<u>Instructions:</u> *We would like to include personal stories to future college algebra students about how current students strengthened their brain in math. Reflect on your life and determine a time when you strengthened your brain in math, particularly when you*

struggled through a difficult concept. In the box below, write a 1-2 paragraph story that includes at least one detailed example.

[Students will have an essay box in which they will type their response.]

Instructions: *Thank you for your response. In the second part of this assignment, read the following material about growth mindsets, and answer the essay question at the end.*

Growth Mindsets

While there is evidence that the human brain can grow, not everyone believes that intelligence can change. People who believe that intelligence can grow are said to have a growth mindset whereas people who believe that intelligence cannot grow are said to have a fixed mindset. There are benefits in believing in a growth mindset. In fact, a study found that for all 10th graders in the country of Chile, students with a growth mindset were 3 times more likely to score in the top 20% of their class whereas students with a fixed mindset were more likely to score in the bottom 20% of their class.

When people with a growth mindset encounter an obstacle or make mistakes, they typically see it as an opportunity for their brains to grow. They know that with enough effort, help from others, and appropriate strategy use, they can get better and smarter, eventually being able to grasp what they need to learn. It is typical for students to encounter challenges in school, and having a growth mindset can help students face obstacles and grow from them.

Some people disagree with the idea of a growth mindset because no matter how much their intelligence grows, they do not believe that their intelligence can ever equal that of a person like their college math professor or Albert Einstein. However, the concept of growth mindset simply is that intelligence grows; with time, help, and effort, people can be smarter than they were before. Rather than comparing themselves with others, growth mindsets encourage people to look at their own intelligence and realize that they have potential to grow smarter each and every day.

What are some ways students can develop a growth mindset in math? If students think that they aren't good at math or they don't understand a math concept, students can address these beliefs by adding the word 'yet' into their thoughts; they aren't good at math yet, or they don't understand a math concept yet.

"I'm not good at math... yet."

This is because regardless of students' current mathematical abilities, they can improve their math intelligence over time by putting in effort, using more effective study strategies, and seeking out help when they are having difficulty. All students make mistakes and fail to understand math concepts sometime along their academic career. An important step to improving math intelligence is to view mistakes and gaps in understanding as a normal part of the learning process. These mistakes and gaps are opportunities to grow, learn, and improve rather than an indication that someone is not a math person or unfit for work that involves math. Math intelligence grows just like a muscle. Every time students are correcting errors in their understanding, reviewing difficult concepts, and practicing homework problems over and over again, they are strengthening their neural connections and growing their math intelligence.

How can students get help and 'learn the right exercises' to strengthen their math intelligence? At [insert institution's name], they have the option of going to [insert options with hyperlinks] to get tutoring. They could also visit their professor's office hours to ask clarifying questions and to determine what other strategies they could use to increase their math intelligence and performance in college algebra. In addition, students can form study groups with their peers and work together to build their math intelligence.

[Insert picture of institution's tutoring lab]

<u>Instructions:</u> *We hope to share this information with students in future college algebra courses who believe that they cannot improve their math intelligence. Instead of receiving information written by instructors, we believe that it would be more beneficial to receive a letter of encouragement from a peer.*

Therefore, using your own words, write a 3-4 paragraph letter to future students in college algebra who believe that they will never be good at math or they can never improve their math intelligence. Include ideas about

- *what a growth mindset is,*
- *the scientific evidence for a growth mindset,*
- *how effort and appropriate strategy use in math can improve math intelligence, and*
- *practical strategies that you think a peer will find helpful in succeeding in college algebra.*

[Students will have an essay box in which they will type their response.]

APPENDIX B: TASK VALUE INTERVENTION

<u>Instructions</u>: *Thank you for your participation in this extra credit opportunity. To receive extra credit, the entire assignment must be fully completed. In this assignment, which will take about 40 minutes to complete, you will read reasons why college algebra could be personally relevant to students. We would like to share this information with future college algebra students, but we want your help in evaluating whether these reasons are truly relevant. Please read the following reasons why taking college algebra could be useful to you, and rate how much you believe in each reason. Afterwards, you will be asked to complete two writing activities.*

Read the following reason, and rate whether the reason represents your beliefs.

Reason 1

Taking college algebra is useful because it will help students earn a college degree. Math is a core requirement, and taking a math course, such as college algebra, is needed for graduation. Having a college degree will open doors to potential careers and salaries that would not be possible without a college education.

1) This reason is [students will have a drop-down box of the following options:]
1 - Very untrue of what I believe
2 - Untrue of what I believe
3 - Somewhat untrue of what I believe
4 - Neutral
5 - Somewhat true of what I believe
6 - True of what I believe
7 - Very true of what I believe

Reason 2

College algebra is useful because it challenges students to create new study habits, recognize when to ask for help from instructors or tutors, and develop persistence, particularly when encountering academic failure. College algebra can be tough because it typically requires time management and a different way of studying than what students are used to for other courses, such as English or science. College algebra gives students an opportunity to challenge themselves and develop as a college student. By striving to make positive choices throughout the course, students are preparing themselves for difficult courses in the future and learning how to be successful in their college career.

2) This reason is [students will have a drop-down box of the following options:]
1 - Very untrue of what I believe
2 - Untrue of what I believe
3 - Somewhat untrue of what I believe
4 - Neutral
5 - Somewhat true of what I believe
6 - True of what I believe
7 - Very true of what I believe

Reason 3

College algebra is useful because it teaches math skills that are needed in future classes. For example, chemistry uses systems of equations to solve for unknown variables. Physics uses quadratic equations to model parabolic situations and to solve various formulas. Economics uses exponential functions to model growth. The topics learned in college algebra will most likely appear in other courses that students take, and having a grasp on the topics now will benefit students in the future.

3) This reason is [students will have a drop-down box of the following options:]
1 - Very untrue of what I believe
2 - Untrue of what I believe
3 - Somewhat untrue of what I believe
4 - Neutral
5 - Somewhat true of what I believe
6 - True of what I believe
7 - Very true of what I believe

Reason 4

College algebra is useful because it helps students develop problem solving and critical thinking skills. Students get to practice and build their problem-solving skills through college algebra assignments by making sense of math problems and deciding which methods are the most efficient and effective ways to solve problems. Generally, students are strengthening their ability to understand the purpose of a problem and evaluate solutions. Building these problem solving and critical thinking skills is important for future courses and careers; college courses will push students to think deeper and problem solve, and higher-paid careers will include tasks that require higher-level thinking. By learning these skills in college algebra, students will be able to transfer their abilities to future courses and careers.

4) This reason is [students will have a drop-down box of the following options:]
1 - Very untrue of what I believe
2 - Untrue of what I believe
3 - Somewhat untrue of what I believe
4 - Neutral
5 - Somewhat true of what I believe
6 - True of what I believe
7 - Very true of what I believe

Reason 5

College algebra is useful because the topics students learn in college algebra can help model real-life situations. In college algebra, functions are a key topic, and students learn about various types, such as linear, quadratic, and exponential functions. These functions can model real-life situations. For example, linear functions can help model the cost of a monthly cell phone bill. Let's say that a cell phone plan costs $75 a month, and the plan includes 10 gigabytes of data. If a person uses more than 10 gigabytes, then the plan will charge $15 for each additional gigabyte. To determine how much the bill is each month, the equation $y = 15x + 75$ can be used to model the cost of the cell phone bill where x is the additional number of gigabyte used and y is the total cost of cell phone bill. Other functions can model other situations; quadratic functions can model the parabolic path of a basketball as the ball is being shot into a hoop, and exponential functions can model the growth in the population. College algebra topics can be applied to the real world, which makes the course useful.

5) This reason is [students will have a drop-down box of the following options:]
1 - Very untrue of what I believe
2 - Untrue of what I believe
3 - Somewhat untrue of what I believe
4 - Neutral
5 - Somewhat true of what I believe
6 - True of what I believe
7 - Very true of what I believe

Reason 6

College algebra is useful because it prepares students to learn numerical skills in the future. Students may not use all the topics they learned in college algebra in their future, but the fact that they have had math courses strengthens their skills with manipulating numbers. When graphs or equations show up in future courses, standardized tests, or careers, college algebra students will know that they have seen similar ideas in the past. It may have been difficult to learn college algebra, but being familiar with college algebra ideas means that students can be confident in their numerical skills and their ability to learn and use math in future situations.

6) This reason is [students will have a drop-down box of the following options:]
1 - Very untrue of what I believe
2 - Untrue of what I believe
3 - Somewhat untrue of what I believe
4 - Neutral
5 - Somewhat true of what I believe
6 - True of what I believe
7 - Very true of what I believe

Thank you for rating the previous six reasons. We believe that future college algebra students will enjoy reading ideas of why college algebra is relevant to their peers.

In this activity, write a 3-4 paragraph letter to a future college algebra student, explaining why learning college algebra is personally relevant to you.

In this letter, you can incorporate any reason that is relevant to you. You may use the reasons you agreed with earlier in this assignment, or you can make up your own reasons. However, you must use your own words and give specific, detailed examples.

[Students will have an essay box in which they will type their response.]

Last, we are also interested in sharing reasons why learning college algebra can be beneficial to others. For example, learning college algebra can lead students to finishing a college degree, which can bring pride to their family or can increase the number of people who are college-educated in society. Also, learning college algebra can help students learn skills that will be useful to share with their friends who are learning similar topics. We need your help in thinking of other reasons that college algebra may be beneficial to others. Please reflect on the following question:

How can ***your*** *learning of college algebra be beneficial to others, such as family, friends, or society?*

Write a 1-2 paragraph essay and include at least one specific, detailed example.

[Students will have an essay box in which they will type their response.]

APPENDIX C: ITEMS INCLUDED ON PRE-SURVEY AND POST-SURVEY

Scale Used for Items 1-37

Strongly Disagree	1
Disagree	2
Somewhat Disagree	3
Neither Agree Or Disagree	4
Somewhat Agree	5
Agree	6
Strongly Agree	7

Items 1-37

1. Your math intelligence is something about you that you can't change very much.
2. You have a certain amount of math intelligence, and you really can't do much to change it.
3. You can learn new things, but you can't really change your math intelligence.
4. I will use the information I learn in my math class in the future.
5. What I learn in my math course will be important for my future occupational success.
6. I will use the information I learn in my math course in other classes I will take in the future.
7. I will not use what I learn in my math course.
8. I expect to do very well in this class.
9. I'm certain I can understand the ideas taught in this course.
10. My study skills are excellent in this class.
11. I think I will receive a good grade in this class.
12. I am certain I can understand the most difficult material presented in this course.
13. I am sure I can do an excellent job on the problems and tasks assigned for this class.
14. It is important to me to be good at math.
15. Being good at math means a lot to me.
16. Good grades in math are very important to me.
17. Performing well in math is important to me.
18. Math is not meaningful to me.
19. Math is very important to me personally.
20. It is important to me to know a lot of math.
21. I care a lot about remembering the things we learn in math.
22. To be honest, I don't care about math.
23. I really care about learning a lot in math.
24. My aim is to avoid doing worse than other students.
25. My goal is to avoid performing poorly compared to others.
26. I am striving to avoid performing worse than others.
27. Dealing with math drains a lot of my energy.
28. Doing math is exhausting to me.
29. Learning math exhausts me.
30. I often feel completely drained after doing math.
31. I'd rather not do math because it only worries me.

32. When I deal with math, I get annoyed.
33. Math is a real burden to me.
34. Doing math makes me really nervous.
35. I'd have to sacrifice a lot of free time to be good at math.
36. I have to give up a lot to do well in math.
37. I have to give up other activities that I like to be successful at math.

Scale Used for Items 38-39

Not at All Likely	1
Slightly Likely	2
Somewhat Likely	3
Very Likely	4
Extremely Likely	5

Items 38-39

Read the following scenario: Pretend that, later today or tomorrow, you got a bad grade on a very important math assignment. Honestly, if that happened, how likely would you be to think these thoughts?

38. I can get a higher score next time if I find a better way to study.
39. This means I'm probably not very smart at math.

APPENDIX D: DEMOGRAPHIC QUESTIONS FOR PRE-SURVEY

40. What is your gender?

____

41. What is your age?

____

42. What is your student classification?

- ☐ First-Year
- ☐ Sophomore
- ☐ Junior
- ☐ Senior
- ☐ Other: _______________

43. What is your ethnicity?

- ☐ Hispanic or Latino
- ☐ Not Hispanic or Latino
- ☐ Unknown

44. What is your race?

- ☐ African American or Black
- ☐ American Indian or Alaska Native
- ☐ Asian
- ☐ Caucasian or White
- ☐ Native Hawaiian or Other Pacific Islander
- ☐ Other: _________________________

45. What is your mother's maximum level of education?

- ☐ No high school
- ☐ Some high school
- ☐ High school diploma or GED
- ☐ Some college
- ☐ Associate degree
- ☐ Bachelor degree
- ☐ Graduate degree
- ☐ I do not know

46. What is your father's maximum level of education?

- ☐ No high school
- ☐ Some high school
- ☐ High school diploma or GED
- ☐ Some college
- ☐ Associate degree
- ☐ Bachelor degree
- ☐ Graduate degree
- ☐ I do not know

47. Have you taken a developmental/remedial math class during college? These classes typically do not count as credit toward your degree. For example, if you took developmental/remedial classes at [insert institution’s name], the course was [insert relevant courses].

- ☐ Yes, I have taken a developmental/remedial math class during college. (e.g. If you took these classes at [insert institution’s name], you would have taken [insert relevant courses].)
- ☐ No, I have not taken a developmental/remedial math class during college.
- ☐ I don't know. Please explain:

  ____

REFERENCES

Acee, T. W., Barry, W. J., Flaggs, D. A., Holschuh, J. P., Daniels, S., & Schrauth, M. (2017). Student-perceived interferences to college and mathematics success. *Journal of Developmental Education, 40*(2), 2-9.

Acee, T. W., & Weinstein, C. E. (2010). Effects of value-reappraisal intervention on statistics students' motivation and performance. *The Journal of Experimental Education, 78*, 487-512. doi: 10.1080/00220970903352753

Adelman, C. (2004). *The empirical curriculum: Changes in postsecondary course-taking, 1972- 2000.* Washington, DC: U.S. Department of Education.

Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions.* Newbury Park, CA: Sage.

Ames, C. (1992). Classrooms: Goals, structures, and student motivation. *Journal of Educational Psychology, 84,* 261–271. doi:10.1037/0022- 0663.84.3.261

Aronson, J., Fried, C. B., & Good, C. (2002). Reducing the effects of stereotype threat on African American college students by shaping theories of intelligence. *Journal of Experimental Social Psychology*, *38*, 113-125. doi: 10.1006/jesp.2001.1491

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory.* Englewood Cliffs, NJ: Prentice Hall.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York, NY: W. H. Freeman.

Barron, K., & Hulleman, C. (2015). Expectancy-value-cost model of motivation. In J. D. Wright (Ed.), *International encyclopedia of the social & behavioral sciences, 2nd ed.,* (pp. 503-509). Oxford: Elsevier.

Biddle, S. J. H., Wang, C. K. J., Chatzisarantis, N. L. D., & Spray, C. M. (2003). Motivation for physical activity in young people: Entity and incremental beliefs about athletic ability. *Journal of Sports Sciences, 21*(12)*,* 973-989. doi:10.1080/02640410310001641377

Blackwell, L. S. (2002). *Psychological mediators of student achievement during the transition to junior high school: The role of implicit theories* (Unpublished doctoral dissertation). Columbia University, New York.

Blackwell, L. S., Rodriguez, S., & Guerra-Carrillo, B. (2015). Intelligence as a malleable construct. In S. Goldstein, D. Princiotta, & J. A. Naglieri (Eds.), *Handbook of intelligence: Evolutionary theory, historical perspective, and current concepts* (pp. 263-282). New York, NY: Springer.

Blackwell, L. S., Trzesniewski, K. H., & Dweck, C. S. (2007). Theories of intelligence and achievement across the junior high school transition: A longitudinal study and an intervention. *Child Development*, *78*, 246-263.

Boaler, J. (2016). *Mathematical mindsets: Unleashing students' potential through creative math, inspiring messages and innovative teaching*. San Francisco, CA: Jossey-Bass.

Bong, M., & Hocevar, D. (2002). Measuring self-efficacy: Multitrait-multimethod comparison of scaling procedures. *Applied Measurement in Education, 15*(2), 143-171.

Brehmer, Y., Westerberg, H., & Backman, L. (2012). Working-memory training in younger and older adults: Training gains, transfer, and maintenance. *Frontiers in Human Neuroscience, 6*, 1-7.

Brown, E. R., Smith, J. L., Thoman, D. B., Allen, J. M., & Muragishi, G. (2015). From bench to bedside: A communal utility value intervention to enhance students' biomedical science motivation. *Journal of Educational Psychology*, *107*(4), 1116-1135. doi: 10.1037/edu0000033

Bryant, F. B. and Yarnold, P. R. (1995) Principal components analysis and exploratory and confirmatory factor analysis. In Grimm, L.G. and Yarnold P.R., Eds., *Reading and understanding multivariate statistics*, American Psychological Association, Washington DC, 99-136.

Burnette, J. L. (2010). Implicit theories of body weight: Entity beliefs can weigh you down. *Personality and Social Psychology Bulletin, 36*(3)*,* 410-422. doi:10.1177/0146167209359768

Burnette, J. L., O'Boyle, E. H., VanEpps, E. M., Pollack, J. M., & Finkel, E. J. (2013). Mind-sets matter: A meta-analytic review of implicit theories and self-regulation. *Psychological Bulletin, 139*(3), 655-701. doi: 10.1037/a0029531

Burns, K. C., & Isbell, L. M. (2007). Promoting malleability is not one size fits all: Priming implicit theories of intelligence as a function of self-theories. *Self and Identity, 6*, 51-63. doi: 10.1080/15298860600823864

Canning, E. A., & Harackiewicz, J. M. (2015). Teach it, don't preach it: The differential effects of directly-communicated and self-generated utility-value information. *Motivation Science*, *1*(1), 47-71. doi: 10.1037/mot0000015

Canning, E. A., Harackiewicz, J. M., Priniski, S. J., Hecht, C. A., Tibbetts, Y., & Hyde, J. S. (2017). Improving performance and retention in introductory biology with a utility-value intervention. *Journal of Educational Psychology*. Advance online publication. doi:10.1037/edu0000244

Carnegie Foundation for the Advancement of Teaching. (2016). *Developmental math.* Retrieved from http://www.carnegiefoundation.org/developmental-math

Ceci, S. J. (1991). How much does schooling influence general intelligence and its cognitive components? A reassessment of the evidence. *Developmental Psychology, 27*(5), 703-722.

Chen, L. H., Chen, M. Y., Lin, M. S., Kee, Y. H., Kuo, C. F., & Shui, S. H. (2008). Implicit theory of athletic ability and self-handicapping in college students. *Psychological Reports, 103*(2)*,* 476-484. doi:10.2466/pr0.103.2.476-484

Chouinard, R., & Roy, N. (2008). Changes in high-school students' competence beliefs, utility value and achievement goals in mathematics. *British Journal of Educational Psychology, 78*, 31-50. doi: 10.1348/000709907X197993

Cohen, G. L., Garcia, J., Purdie-Vaughns, V., Apfel, N., & Brzustoski, P. (2009). Recursive processes in self-affirmation: Intervening to close the minority achievement gap. *Science*, *324*, 400-403.

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior.* New York, NY: Plenum Press.

Diseth, A., Meland, E., & Breidablik, H. J. (2014). Self-beliefs among students: Grade level and gender differences in self-esteem, self-efficacy and implicit theories of intelligence. *Learning and Individual Differences, 35*, 1-8. doi: 10.1016/j.lindif.2014.06.003

Draganski, B., Gaser, C., Busch, V., Schuierer, G., Bogdahn, U., & May, A. (2004). Neuroplasticity: Changes in grey matter induced by training. *Nature*, *427*, 311–312.

Durik, A. M., Shechter, O. G., Noh, M., Rozek, C. S., & Harackiewicz. (2014). What if I can't? Success expectancies moderate the effects of utility value information on situational interest and performance. *Motivation & Emotion, 39*, 104-118. doi: 10.1007/s11031-014-9419-0

Dweck, C. S. (1986). Motivational processes affecting learning. *American Psychologist, 41*(10), 1040-1048.

Dweck, C. S. (2000). Self-theories: Their role in motivation, personalities, and development. Philadelphia, PA: Psychology Press.

Dweck, C. S., Chiu, C., & Hong, Y. (1995). Implicit theories and their role in judgments and reactions: A world from two perspectives. *Psychological Inquiry, 6*(4), 267-285.

Dweck, C. S., & Leggett, E. L. (1998). A social-cognitive approach to motivation and personality. *Psychological Review, 95*(2), 256-273.

Eccles, J. S. & Wigfield, A. (1995). In the mind of the actor: The structure of adolescents' academic achievement related-beliefs and self-perceptions. *Personality and Social Psychology Bulletin, 21*(3), 215-225.

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Reviews of Psychology, 53*, 109-32.

Eccles, J. S., O'Neill, S. A., & Wigfield, A. (2005). Ability self-perceptions and subjective task values in adolescents and children. In K. A. Moore & L. H. Lippman (Eds.), *What do children need to flourish? Conceptualizing and measuring indicators of positive development* (pp. 237-249). Boston, MA: Springer.

Elliot, A. J., & Murayama, K. (2008). On the measurement of achievement goals: Critique, illustration, and application. *Journal of Educational Psychology, 100*(3), 613-628. doi: 10.1037/0022-0663.100.3.613

Gaspard, H., Dicke, A.-L., Flunger, B., Schreier, B., Häfner, I., Trautwein, U., & Nagengast, B. (2014). More value through greater differentiation: Gender differences in value beliefs about math. *Journal of Educational Psychology, 107*(3), 663-677. doi: 10.1037/edu0000003

Gaspard, H., Dicke, A.-L., Flunger, B., Brisson, B. M., Häfner, I., Nagengast, B., & Trautwein, U. (2015). Fostering adolescents' value beliefs for mathematics with a relevance intervention in the classroom. *Developmental psychology, 51*(9), 1226-1240. doi: 10.1037/dev0000028

Goldstein, S. (2015). The evolution of intelligence. In S. Goldstein, D. Princiotta, & J. A. Naglieri (Eds.), *Handbook of intelligence: Evolutionary theory, historical perspective, and current concepts* (pp. 3-7). New York, NY: Springer.

Good, C., Aronson, J., & Inzlicht, M. (2003). Improving adolescents' standardized test performance: An intervention to reduce the effects of stereotype threat. *Journal of Applied Developmental Psychology*, *24*, 645–662.

Harackiewicz, J. M., & Priniski, S. J. (2018). Improving student outcomes in higher education: The science of targeted intervention. *Annual Review of Psychology, 69*, 409-35. doi:10.1146/annurev-psych-122216-011725

Harackiewicz, J. M., Canning, E. A., Tibbetts, Y., Priniski, S. J., & Hyde, J. S. (2015). Closing achievement gaps with a utility-value intervention: Disentangling race and social class. *Journal of Personality and Social Psychology*. Advance online publication. doi: 10.1037/pspp0000075

Harrison, M. A., Meister, D. G., & LeFevre, A. J. (2011). Which students complete extra-credit work? *College Student Journal*, *45*(3), 550-555.

Herriott, S. R. (2006). Changes in college algebra. In N. Baxter Hastings, F. S. Gordon, S. P. Gordon, & J. Narayan (Eds.), *A fresh start for collegiate mathematics: Rethinking the courses below calculus* (pp. 90-100). Washington, DC: The Mathematical Association of America.

Herriott, S. R., & Dunbar, S. R. (2009). Who takes college algebra? *PRIMUS*, *19*(1), 74-87. doi: 10.1080/10511970701573441

Herron, S., Gandy, R., Ye, N., & Syed, N. (2012). A comparison of computer-assisted and traditional college algebra instruction. *The Journal of Computers in Mathematics and Science Teaching, 31*(3), 249-258.

Hong, Y., Chiu, C., Dweck, C. S., Lin, D., & Wan, W. (1999). Implicit theories, attributions, and coping: A meaning system approach. *Journal of Personality and Social Psychology*, *77*(3), 588–599.

Hopf, F., Sears, R., Torres-Ayala, A., & Maher, M. (2015). College algebra redesigned: Opening doors to success. *MathAMATYC Educator, 6*(2), 8-12.

Hoyt, C. L., Burnette, J. L., & Innella, A. N. (2012). I can do that: The impact of implicit theories on leadership role model effectiveness. *Personality and Social Psychology Bulletin, 38*(2)*,* 257-268. doi:10.1177/0146167211427922

Hulleman, C. S., Godes, O., Hendricks, B. L., & Harackiewicz, J. M. (2010). Enhancing interest and performance with a utility value intervention. *Journal of Educational Psychology*, 102(4), 880-895. doi: 10.1037/a0019506

Hulleman, C. S., & Harackiewicz, J. M. (2009). Promoting interest and performance in high school science classes. *Science*, 326, 1410-1412. doi: 10.1126/science.1177067

Hulleman, C. S., Kosovich, J. J., Barron, K. E., & Daniel, D. B. (2016). Making connections: Replicating and extending the utility value intervention in the classroom. *Journal of Educational Psychology,* 1-19. doi: 10.1037/edu0000146

Husman, J., Derryberry, P.W., Crowson, M.H., & Lomax, R. (2004). Instrumentality, task value, and intrinsic motivation: Making sense of their independent interdependence. *Contemporary Educational Psychology, 29*(1), 63–76. doi: 10.1016/S0361-476X(03)00019-5

Ichinose, C., & Clinkenbeard, J. (2016). Flipping college algebra: Effects on student engagement and achievement. *Learning Assistance Review (TLAR), 21*(1), 115-129.

Job, V., Dweck, C. S., & Walton, G. M. (2010). Ego depletion—Is it all in your head? Implicit theories about willpower affect self-regulation. *Psychological Science, 21*(11)*,* 1686-1693. doi:10.1177/ 0956797610384745

Kray, L. J., & Haselhuhn, M. P. (2007). Implicit negotiation beliefs and performance: Experimental and longitudinal evidence. *Journal of Personality and Social Psychology, 93*(1)*,* 49-64. doi:10.1037/0022-3514.93.1.49

Luttrell, V. R., Callen, B. W., Allen, C. S., Wood, M. D., Deeds, D. G., & Richard, D. C. S. (2010). The Mathematics Value Inventory for general education students: Development and initial validation. *Educational and Psychological Measurement, 70*(1), 142-160. doi: 10.1177/0013164409344526

Mackey, A., Miller-Singley, A., & Bunge, S. (2013). Intensive reasoning training alters patterns of brain connectivity at rest. *Journal of Neuroscience*, 33(11), 4796–4803.

Mangels, J. A., Butterfield, B., Lamb, J., Good, C., & Dweck, C. S. (2006). Why do beliefs about intelligence influence learning success? A social cognitive neuroscience model. *Social Cognitive & Affective Neuroscience, 1*(2)*,* 75-86. doi:10.1093/scan/nsl013

Mireles, S. V., Acee, T. W., & Gerber, L. N. (2014). FOCUS: Sustainable mathematics successes. *Journal of Developmental Education, 38*(1), 26-36.

Mueller, C. M., & Dweck, C. S. (1998). Praise for intelligence can undermine children's motivation and performance. *Journal of Personality and Social Psychology*, *75*, 33–52.

Nicholls, J. G. (1984). Achievement motivation: Conceptions of ability, subjective experience, task choice, and performance. *Psychological Review*, *91*(3), 328-346. doi: 10.1037/0033-295X.91.3.328

Nussbaum, A. D., & Dweck, C. S. (2008). Defensiveness versus remediation: Self-theories and modes of self-esteem maintenance. *Personality and Social Psychology Bulletin, 34*(5), 599-612. doi: 10.1177/0146167207312960

Oettingen, G., Pak, H., & Schnetter, K. (2001). Self-regulation of goal setting: Turning free fantasies about the future into binding goals. *Journal of Personality Psychology, 80* (5)*,* 736-753.

Oyserman, D., Bybee, D., & Terry, K. (2006). Possible selves and academic outcomes: How and when possible selves impel action. *Journal of Personality and Social Psychology*, *91*, 188–204.

Pajares, F., & Miller, M. D. (1995). Mathematics self-efficacy and mathematics performances: The need for specificity of assessment. *Journal of Counseling Psychology, 42*(2), 190-198. doi:10.1037/0022-0167.42.2.190

Park, D., & Kim, S. (2015). Time to move on? When entity theorists perform better than incremental theorists. *Personality and Social Psychology Bulletin, 41*(5), 736-748. doi: 10.1177/0146167215578028

Paunesku, D., Walton, G. M., Romero, C., Smith, E., Yeager, D., & Dweck, C. (2015). Mind-set interventions are a scalable treatment for academic underachievement. *Psychological Science, 26*(6), 784-793. doi: 10.1177/0956797615571017

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology, 82*(1), 33-40.

Reyes, C. (2010). Success in algebra among community college students. *Community College Journal of Research and Practice*, *34*(3), 256-266. doi: 10.1080/10668920802505538

Robins, R. W., & Pals, J. L. (2002). Implicit self-theories in the academic domain: Implications for goal orientation, attributions, affect, and self-esteem change. *Self and Identity, 1*, 313-336. doi: 10.1080/15298860290106805

RTI International. (2015). *Completion of gatekeeper math: United States.* Retrieved from http://www.completionarch.org/arch/indicator/3CM-11-EGC-US

Rutschow, E. Z., & Schneider, E. (2011). Unlocking the gate: What we know about improving developmental education. Retrieved from www.mdrc.org/sites/default/files/full_595.pdf

Schunk, D. H., Meece, J. L., & Pintrich, P. R. (2014). *Motivation in education: Theory, research, and applications* (4th ed.). Upper Saddle River, NJ: Pearson.

Shechter, O. G., Durik, A. M., Miyamoto, Y., & Harackiewicz, J. M. (2011). The role of utility value in achievement behavior: The importance of culture. *Personality and Social Bulletin*, 37(3), 303-317. doi: 10.1177/0146167210396380

Shively, R. L., & Ryan, C. S. (2013). Longitudinal changes in college math students' implicit theories of intelligence. *Social Psychology of Education, 16*, 241-256. doi: 10.1007/s11218-012-9208-0

Silva, F. J., & Gross, T. F. (2004). The rich get richer: Students' discounting of hypothetical delayed rewards and real effortful extra credit. *Psychonomic Bulletin & Review, 11*(6), 1124-1128.

Trautwein, U., Marsh, H.W., Nagengast, B., Ludtke, O., Nagy, G., & Jonkmann, K. (2012). Probing for the multiplicative term in modern expectancy-value theory: A latent interaction modeling study. *Journal of Educational Psychology*, *104*(3), 763–777. doi: 10.1037/a0027470

Trautwein, U., Nagengast, B., Marsh, H.W., Gaspard, H., Dicke, A.-L., Ludtke, O., & Jonkmann, K. (2013). Expectancy-value theory revisited: From expectancy-value theory to expectancy-values theory? In D. M. McInerney, H. W. Marsh, & R. Craven (Eds.), *Theory driving research: New wave perspectives on self-processes and human development* (pp. 233-249). Charlotte, NC: Information Age Publishing.

Weiner, B. (2010). The development of an attribution-based theory of motivation: A history of ideas. *Educational Psychologist, 45*(1), 28-36. doi: 10.1080/00461520903433596

West, M. R., Kraft, M. A., Finn, A. S., Martin, R. E., Duckworth, A. L., Gabrieli, C. F. O., Gabrieli, J. D. E. (2016). Promise and paradox: Measuring students' non-cognitive skills and the impact on schooling. *Educational Evaluation and Policy Analysis, 38*(1), 148-170. doi: 10.3102/0162373715597298

Wigfield, A. (1994). Expectancy-value theory of achievement motivation: A developmental perspective. *Educational Psychology Review, 6*(1), 49-78.

Wigfield, A., & Cambria, J. (2010). Students' achievement values, goal orientations, and interest: Definitions, development, and relations to achievement outcomes. *Developmental Review, 30*, 1-35. doi: 10.1016/j.dr.2009.12.001

Wigfield, A., & Eccles, J. S. (2002). The development of competence beliefs, expectancies for success, and achievement values from childhood through adolescence. In A. Wigfield & J. S. Eccles (Eds.), *Development of achievement motivation* (pp. 91-120). San Diego, CA: Academic Press.

Wilson, T. D., & Linville, P. W. (1982). Improving the academic performance of college freshmen: Attribution therapy revisited. *Journal of Personality and Social Psychology*, *42*, 367–376.

Yanai, H., & Ichikawa, M. (2007). Factor analysis. In C. R. Rao & S. Sinharay (Eds.), *Handbook of Statistics: Vol. 26. Psychometrics* (pp. 257-296). doi:10.1016/S0169-7161(06)26009-7

Yeager, D. S., & Dweck, C. (2012). Mindsets that promote resilience: When students believe that personal characteristics can be developed. *Educational Psychologist, 47*(4), 303, 314.

Yeager, D. S., & Walton, G. M. (2011). Social-psychological interventions in education: They're not magic. *Review of Educational Research, 81*(2), 267-301.

Yeager, D. S., Romero, C., Paunesku, D., Hulleman, C, Schneider, B., Hinojosa, C., . . . Dweck, C. S. (2016). Using design thinking to improve psychological intervention: The case of growth mindset during the transition to high school. *Journal of Educational Psychology, 108*(3), 374-391. doi: 10.1037/edu0000098