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Implicit Theories of Intelligence and Learning a Novel Mathematics Task

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A NOVEL MATHEMATICS TASK

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ABSTRACT

Implicit Theories of Intelligence and Learning a Novel Mathematics Task

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The social-cognitive model of motivation states that students adopt a theory of the nature of intelligence that guides their goals in academia and their responses to academic setbacks. Students who believe intelligence is an unchanging entity within them are more likely to adopt goals to display high ability, hide low ability, and respond helplessly to failed schoolwork. Conversely, a student who believes intelligence is a measure of effort and persistence will be motivated to gather knowledge and acquire new skills. The current study investigated the role theories of intelligence play in the field of mathematics understanding. In two experiments, participants either taught themselves or were explicitly taught how to solve a novel math task. It was hypothesized that participants who believe intelligence is a malleable trait (i.e., based on effort) would engage more in teaching themselves the correct solution and experience fewer attitude-related cognitive disruptions during a test of the new math procedure. However, attitudes from the social-cognitive model of motivation were only found to influence behavior and test performance when analyses also included the influence of an effect similar to a stereotype threat among female participants. Although not all hypotheses and goals of the thesis were confirmed, results could help develop research that explains the cognitive

mechanisms of mathematics anxiety and threats to stereotype within the field of mathematics cognition.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Mainstream cognitive psychology has been hesitant to turn to factors affecting performance that can best be explained by attitudinal or motivational variables. It is a basic assumption in the laboratory setting that participants will fully engage themselves in the experimental task. It is also a leap of faith to suggest that this engagement exists when the same cognitive processes are applied to everyday tasks. Is it reasonable to assume that people put the same level of motivation into memorizing a list of words for a research credit as they may apply to memorizing a list of items to purchase at the grocery store? However if these assumptions of engagement and ecological validity are removed, what variables can be added that will explain these individual differences, that until recently have been cast off as inconvenient fluctuations in the data?

The realm of mathematical cognition in recent decades has focused more on the relevance of affect and motivation and their impact on math performance (Ashcraft & Rudig, 2012). Recently, math cognition research has revealed consistent effects on performance from affective factors, such as math anxiety, math self-efficacy, math self-concept, interest, and threats to stereotype. Each construct on its own does well to predict performance; however, there lacks an overarching framework to explain the constellations of positive and negative affect. High-achieving students seem to have the right combination of attitudes that foster development and learning in mathematics, while low-achieving students succumb to a host of attitudes that create barriers to mathematical understanding.

The aim of this thesis was to establish the social-cognitive model of motivation (Dweck & Legget, 1988) as an explanation for the mechanisms that affective states, e.g., math anxiety and stereotype threat, create in mathematics cognition. Specifically, this explanation suggests that students' attributions concerning the nature of abilities in mathematics predict the manifestation, development, and effects of the constellation of attitudes towards mathematics. Two experiments tested this framework by examining the role that the social-cognitive model of motivation has in explaining differences in learning and performance to a novel mathematics task in a college population.

Social-Cognitive Model of Motivation

The social-cognitive model of motivation is a conceptual framework originally formulated by Dweck and Legget (1988) to explain the differentiable, yet consistent, patterns of academic behavior between two types of students. In this model, a student's belief about the nature of intelligence and academic ability leads to specific goals in academia, which in turn elicit precise responses to setbacks in schoolwork and tests. I will first explain the initial motivation theories that led to Dweck's formulation, and then I will further detail the motivational patterns of beliefs, goals, and behaviors in academia.

Background

Much of the research on achievement and motivation in academia began with Weiner's (1985) attribution-based theory of motivation. Wiener found consistent trends in behavior, depending on whether students had internal or external loci of control (see review in Weiner, 2010). The group of students with the lowest achievement tended to attribute failures to stable, internal events, like ability or intelligence, and attribute successes to unstable, external events (e.g., good luck). It was as if these students felt helpless in controlling their academic fate. In contrast, the group of students with the highest achievement would instead attribute both their successes and failures to unstable, internal events such as effort and persistence. In this group of students, success and failure was completely within their control.

Dweck's (1988) social-cognitive model of motivation builds on Weiner's (2010) attribution-based theory of motivation. That is, academic motivation is based on the attributions of failures and successes, and then incorporating the stability of these causes. However, the social-cognitive model goes further by linking the attribution to the subsequent pursuit of academic goals and responses to failures that students face. Specifically, Dweck took the attribution framework and combined it with her earlier research on learned helplessness (Dweck, 1975) and a concept known as *fear of failure*, in which students with both low and high achievement are paralyzed from fear that a bad score on a test signifies low personal worth or competence (Beery, 1975). The social-cognitive model integrates academic goals, either performance-judgment goals or learning-development goals, to strengthen the causal link between attributions and fear of failure. Simply put, the social-cognitive model states that attributions about success and failure guide a student to approach academia with the aim of avoiding judgment on performance, which leads to behaviors such as fear of failure and learned helplessness. The sections below will reinforce the connectivity of these ideas and the strength of the social-cognitive model to explain both positive and negative academic behaviors.

Implicit Theories of Intelligence

The implicit theories of intelligence are the foundation of the social-cognitive model of motivation; they serve as the attribution benchmarks for explaining the foundations of intelligence, ability, and personal worth (Dweck, 1999; Dweck & Legget, 1988). Students fall along a continuum when explaining the nature of intelligence. On one end, students believe that intelligence is an entity within them that cannot change. This is also referred to as the *fixed* or *entity* belief of intelligence. According to this view, intelligence is a trait that is decided upon at birth; people may have high abilities in one area and low abilities in another, and there is nothing they can do to change that (Dweck, 1999; Dweck & Legget, 1988). Tests of intelligence and abilities become measures of stable internal qualities of the individual. A test of mathematics is not a test of current conceptual understanding, but of innate mathematical talent. When following this philosophy, the life pursuit then becomes to find those areas in life that they were born to succeed in and avoid the ones where they would ultimately fail. For example, some students may believe that they have a natural talent for art, were not born to understand mathematics and science, and would not consider mathematics or science for possible careers.

On the other side of the continuum, intelligence is no longer an indication of competence, but of current understanding and effort. Students on this end of the spectrum believe intelligence to be malleable and something that can change by building knowledge or increasing effort (Dweck, 1999; Dweck & Legget, 1988). This view is referred to as the *incremental* or *malleable* belief of intelligence. Students with a malleable belief will interpret a high score on a test to mean that they have acquired the proper knowledge base and had put forth an acceptable amount of effort. Therefore, low test scores suggest a lack of knowledge and a lack of the effort necessary to succeed. Relating this attitude back to theories of attribution, students with incremental beliefs attribute internal, unstable causes to academia, causes that are personally controllable.

These ideas were illustrated in a study conducted by In Hong, Chiu, Dweck, Lin, and Win (1999). In this study, participants self-reported their attitudes about the changeability of intelligence; that is, they reported the degree to which they supported an entity or incremental view of intelligence. After this, they were given an exam and immediately were provided with a fabricated output of their results, indicating low performance compared to another confederate participant. In a follow-up questionnaire, the participants provided explanations for their poor performance. Participants that ascribed to the entity view in the implicit theories scale gave fixed-ability and low intelligence justifications for their low performance, whereas, incremental theorists alluded to low effort to explain their poor performance.

Even though students can explicitly state these beliefs in a routine questionnaire, the theories of intelligence are implicit, because students are unaware of the impact these beliefs have in driving attitudes and behavior in academia; this idea will be described in further detail below. Also, entity or incremental theories of intelligence can be implicitly primed by reading short passages that endorse intelligence and abilities as either fixed or malleable traits (Burns & Isbell, 2007; Hong, et al., 1999; Murphy & Dweck, 2010).

The mechanism of priming implicit theories of intelligence is effective because students, whether they have an entity or incremental perspective, view intelligence as a combination of both effort and ability and not as an all-or-none dichotomy. Mueller and

Dweck (1997, as cited in Dweck, 1999) asked college students to fill in values for the equation, "Intelligence = _____% effort + _____% ability." Students with an incremental perspective placed more emphasis on effort, roughly 65%, whereas students with an entity perspective placed 65% weight on ability. While having an entity view of intelligence makes students more likely to look to ability and fixed traits for explanations of intelligence, they may still maintain a view that effort can lead to a small increase in ability (Ablard & Mills, 1996; Dweck & Legget, 1988; Dweck, 1999; Mueller & Dweck, 1998). Therefore, retraining attribution can temporarily shift the focus for the causes of intelligence to become either dominated by effort or ability inferences. Despite the malleability of implicit theories of intelligence, they become stable in grade school and continue to stabilize onto adulthood (Stipek & Gralinski, 1996; Robins & Pals, 2002).

Performance vs. Learning Goals

The different implicit theories of intelligence lead to contrasting aims, pursuits, or goals in academia (Dweck & Legget, 1988). Students who believe intelligence is a fixed trait (i.e. entity perspective) will view schoolwork and testing as displays of performance and subject to judgment. Those students who believe intelligence is malleable (i.e. incremental perspective) believe schoolwork and testing is an opportunity for growth, learning, and development.

Entity students more frequently champion performance goals. Because intelligence to these students is unchanging, schoolwork and examinations become permanent reflections of their intellectual competence. Low or high scores on a test will signify low or high intelligence, respectively. It is important to note, that entity students interpret test scores as not just a current assessment, but as an indication of future capabilities in that academic domain, regardless of effort or instruction.

Recall that theories of intelligence do not account for ability; that is, entity or incremental students can still have low or high ability. Because of this ability split, performance goals can be divided further into two levels of achievement motivation, classified as either avoidance or approach. Students with low self-efficacy (i.e. they believe in or are aware of their low abilities) will display performance-avoidance goals. They want to avoid showcasing their unsatisfactory performance and avoid revealing to themselves or others that they have low intelligence; because to an entity theorist, low ability reflects as low worth and overall competence. If a student has high self-efficacy, then they will wish to show off those abilities via a performance-approach goal. Again, the goal for this group is to show others and themselves their high level of intelligence or high competence. An entity theorist will likely have performance-approach goals for those subjects they excel at and simultaneously demonstrate performance-avoidance goals for subjects for which they are less confident.

Students with incremental theories of intelligence are more likely to have learning goals in academia. Here, intelligence changes as a reflection of effort and understanding. Therefore, schoolwork and testing do not represent permanent internal competence of the individual, only an indication of the effort and use of problem-solving techniques. The goal then becomes to learn new strategies and develop more knowledge. Self-efficacy in these students interacts differently with the learning goals than it did in performance goals for students with an entity belief. Within incremental beliefs, low self-efficacy is a temporary state that can be changed by learning more; thus, the goal is a learning-approach goal. In situations of high self-efficacy, incremental students maintain a learning-approach goal. They have high self-efficacy because they have put forth effort, and they recognize that they need to continue with that effort to retain high abilities. Regardless of ability level, students with incremental attitudes adopt learning-approach goals in academia.

Bempechat and London (1991) investigated these ideas by introducing fifth and sixth graders to an ability called "Matrix Ability" where one group was told the ability was a fixed trait in which some kids have it and others do not (i.e. the fixed ability group), and another group of students were told that matrix ability could be improved upon with practice (i.e. the malleable ability group). After receiving poor feedback on a set of Raven's Progressive Matrices, students were then given four goal choices in solving another set of matrices. Three of the choices were performance goals (e.g., problems that are easy or make them look smart), and one was a learning goal (i.e., problems that they will learn from). Students reading the malleable matrix ability passage were significantly more likely to choose the learning goal over any of the performance goals compared to the fixed matrix ability students who overwhelmingly chose performance goals. Understanding ability as a trait that can change led students to adopt goals that served to increase those abilities.

A similar study on fifth graders also used Raven's Progressive Matrices to assess the connection between theories of intelligence and academic goals. Mueller and Dweck (1998) had students solve an initial set of problems followed by fabricated positive feedback. One group of students was praised on their ability for their high performance (e.g., "you must be smart"), and another group was praised on their effort (e.g., "you must have worked hard"). Students were then given the option to pursue different academic goals. Those praised for their intelligence pursued performance goals, compared to students praised for their effort who adopted learning goals. Follow-up experiments found that students praised with intelligence inflated their performance to peers and preferred a choice to read a report of others' performance instead of an option to learn new problem-solving strategies. In contrast, a large majority of the students praised on effort opted for learning new strategies. Believing ability to be a measure of a fixed intelligence leads children to pursue goals focused on performance and to adopt attitudes based on judgment of that ability by others; students viewing ability as a measure of effort instead looked for opportunities to gain knowledge, increase effort, and learn new problem-solving strategies.

To complete the 2 x 2 framework for achievement goal and motivation patterns, there are rare instances of learning-avoidance goals (Elliot, 1999; Elliot & McGregor, 2001). This goal is more relevant to the athletic domain as opposed to a scholastic domain (Ciani & Sheldon, 2010). The idea is that an incremental theorist will avoid effort or persistence that could reinforce a bad habit (e.g. the delicate mechanics of a golf swing). However, this idea seems to have little practicality in schoolwork. It would be like purposefully avoiding an opportunity to learn a new mathematics technique to find the roots of a quadratic equation (e.g., the quadratic formula) because it might affect one's ability to use an older technique (e.g., completing the square). Because this construct is rare and nebulous in academia (Baranik, Stanley, Bynum, & Lance, 2010), the current study did not include learning-avoidance goals in the testing or analysis.

To summarize thus far the research has demonstrated that students with entity beliefs of intelligence overwhelmingly adopt goals centered on displays of performance. Specifically, these students will wish to approach performance judgments to demonstrate their high ability, or will avoid displays of performance to avoid appearing unintelligent. Conversely, students who view assessments as a measure of effort and temporary knowledge will approach school to learn and develop that knowledge, regardless of low or high ability.

Helpless vs. Mastery

Despite students' intelligence belief or goals in academia, many will ultimately face challenges, setbacks, and failures. The nature of education, to challenge students' knowledge, establishes barriers to progress that even students with high ability must overcome. Because students have different beliefs about intelligence and different goals, they will respond differently to these academic failures. Students with entity beliefs of intelligence feel that failures signify low ability, a trait that cannot be changed, and therefore they may respond helplessly. In this scenario, they would withdraw effort and avoid tasks related to the scholastic domain, perhaps retreating to a high self-efficacious domain (Dweck & Legget, 1988). This type of behavior prevents the student from adequately gaining knowledge or learning new strategies, which could effectively halt any academic progress or possibly lead to students switching their college major (Zuckerman, Gagne, & Nafshi, 2001).

Students that interpret intelligence as a measure of effort and knowledge will instead be likely to perceive failure as a momentary lack of effort or absence of effective problem-solving. In this scenario, the behavioral response is then mastery-oriented. These students will double their efforts and persist until they have mastered the material or learned the proper techniques (Dweck & Legget, 1988). It is clear how this behavioral response is more advantageous to succeeding in academia than the helpless behaviors. To overcome failure, a student must learn the knowledge of successful strategies or use effort and persistence to find a new solution. Both of these behaviors are characteristic of students with malleable theories of intelligence, learning goals, and mastery-oriented responses to failure.

To examine these ideas, Licht and Dweck (1984) introduced elementary students to novel psychology concepts via a booklet divided into five sections each containing new material. Most sections were easily understood by all students; however, one group of students read a particular section in an easily understood format, and another group instead read that section presented in syntactically difficult passages. At the end of the task, students were given a mastery test of seven questions covering material from only the easily understood sections. In other words, the questions testing mastery of the material only came from the sections that were easily read by both groups; students in the confusing group were not tested on the confusing material.

In the non-confusing group, there were no differences between the entity and incremental theories of intelligence on the seven-question mastery test. That is, believing intelligence to be a fixed entity or a malleable trait does not interfere with the mastery of novel, easily understood concepts. However, in the confusing group, students with entity theories of intelligence had significantly lower performance than students with an incremental theory of intelligence; in addition, students with incremental beliefs displayed the same level of mastery regardless if they had read confusing or non-confusing passages. This shows that students who perceive intelligence as a fixed ability interpret confusing passages as an indication of a low ability that cannot be changed; in response, they disengage and withdraw effort on subsequent tasks. However, students with incremental beliefs who are reading confusing passages may still infer a low ability, but maintain the idea that persistence will change a low ability into mastery, which is what the results of this experiment demonstrate.

In another study examining these types of responses, Hong, Chiu, Dweck, Lin, and Win (1999) found that students within a Hong Kong university who failed a required English proficiency examination differed in their willingness to enroll in remedial coursework dependent upon their theory of intelligence. Students with an entity theory of intelligence were less likely to enroll in remedial coursework; students subscribing to incremental beliefs were more likely to enroll in remedial classes. Students with entity theories responded helplessly to failure and did not see the utility in persisting to increase English proficiency after a display of low ability. In a follow-up study, participants' theories of intelligence were manipulated by reading a passage from an article espousing either the fixed or malleable nature of intelligence. After receiving poor feedback on an intelligence test, participants were given the option to perform a tutorial exercise that would improve their performance on the next set of trials or an unrelated ability task while the experimenter prepared the next set of trials. Seventy percent of students who read the *Psychology Today* paragraph championing incremental intelligence opted to take the tutorial exercise compared to only 13% of students who read the entity-priming paragraph. Students operating on entity theories are more likely to withdraw from a low ability task, and discount the effectiveness of effort in improving ability. Considering the difficult and sometimes confusing concepts found in mathematics instruction, the math cognition research would expect to find similar effects; entity theorists disengaging from math instruction because being confused by instruction material indicates low ability.

To summarize the social-cognitive model of motivation (see Dweck & Legget, 1988), students' goals and behaviors in school begin with implicit theories of intelligence triggering the pursuit of goals in academia. Entity theories, believing intelligence is fixed, guide individuals to display instances of high intelligence and hide instances of low intelligence, referred to as performance goals. Incremental theories, interpreting intelligence as a measure of effort and knowledge, lead students to continuously improve upon their understanding and problem-solving techniques, referred to as learning goals.

The model continues, stating that academic goals produce responses to failure and setbacks within academia. Students who adopt performance goals interpret failures as indicators of low abilities that cannot be improved upon; therefore, these students respond helplessly by withdrawing from the task domain and, if possible, retreat to a higher self-efficacious task. In contrast, students who endorse learning goals attribute failure to low effort and poor understanding; thus, incremental students respond to failure by increasing effort and by developing their knowledge about the task. The strength of social-cognitive model of motivation in explaining the connection among beliefs, goals, and behavior in academia has been replicated in multiple educational settings (Blackwell, Trzesniewski, & Dweck, 2007; Robins & Pals, 2002; Roedel & Schraw, 1995; Stipek & Gralinski, 1996).

Social-Cognitive Model of Motivation and Affect

Dweck and Legget (1988) described their social-cognitive model of motivation as the way "personality variables can translate into dynamic motivational processes to produce major patterns of cognition, affect, and behavior" (p. 271). So far, the research on this model has focused mostly on patterns of behavior, largely ignoring the major patterns of either cognition or affect. Affects such as self-efficacy and interest have been explored, but only as moderators and mediators linking the motivational variables to measurements of performance and ability. Only recently has the model been theorized to explain the origin of affective states such as math anxiety and stereotype threat (Gunderson, Ramirez, Levine, Beilock, 2012). Once theories of intelligence, academic goals, and responses to failure are linked to the onset and triggers of anxiety and stereotype threat, then the experimentally supported online cognitive explanations that apply to these emotional states can also be applied to the motivational variables.

Mathematics Anxiety

In order for the social-cognitive model of motivation to adequately explain the mechanism in which attitude affects mathematical ability, it has to account for the body of literature linking mathematics anxiety to deficits in mathematical performance. For several decades, math anxiety, fear and apprehensions specific to math-related situations, has been targeted as the main affective barrier to math instruction. Many studies found strong connections between the level of math anxiety and the degree of math performance and math attitudes across childhood, adolescents, and adulthood (see Hembree, 1990). The connections between math anxiety and math-related phenomena are almost exclusively negative; the correlations are -.65 for math self-efficacy, -.47 for enjoyment of math, -.31 for math achievement, and -.27 with course grades (all of these correlations are from college population; grades 5-12 are typically stronger). The relationship is clear; having high math anxiety is detrimental to fostering positive attitudes and ability in math.

One theory of the strong negative relationship between math anxiety and math performance purports that the highly math anxious adopt a global avoidance strategy concerning math. That is, individuals with high math anxiety attempt to avoid the very thing that makes them anxious; in doing so, they fail to learn effective math problem-solving techniques, fall quickly behind in an intensely vertical (i.e., cumulative) academic subject, and deny themselves opportunities to reassess their negative math attitudes. Hembree's (1990) meta-analysis certainly confirms this. Math anxiety is negatively correlated with the intent to take math classes, $r = -.32$, and highly math anxious students report taking fewer math classes, avoiding mathematically-oriented college majors, and passing up math-intensive career paths.

Unfortunately for the high math anxious, primary and secondary school curricula still require extensive math education, and even college instruction involves a minimum math core requirement. Students are being exposed to the material, and are demonstrating enough ability to advance their education. The global avoidance explanation is not sufficient to explain math performance deficits. To address this concern, Ashcraft and Faust (1994) hypothesized that math anxiety is disrupting cognitive processes and affecting computational efficiency while performing a math task. Participants were shown blocks of addition, multiplication, and mixed arithmetic. After separating participants into groups based on their math anxiety level, Ashcraft and Faust found that on simple problems that rely mostly on retrieving answers, there were no performance differences among the anxiety groups. However, when problems became more difficult (e.g., involving carrying or borrowing operations that required more working memory resources), the participants with higher anxiety increased their latencies significantly. Participants with high anxiety also had a diminished ability to reject false answers on larger problems only, also indicating disruptions in their ability to efficiently apply well-learned problem-solving techniques because of a reduction in cognitive resources.

Ashcraft and Kirk (2001) followed up this research by directly influencing working memory resources in a dual-task setting. Participants with different levels of math anxiety had similar levels of performance on single- and two-digit addition problems in control or minimal load conditions; yet, when working memory was taxed with a 6 letter-recall load, the high math anxious participants produced the most errors when addition problems required more computational processing in the form of a carry operation. These results support the conclusion that performance deficits in high math anxiety do not stem from a lack of effective problem solving techniques, but instead from a disruption in cognitive resources necessary for immediate, on-line computation. In a similar study, subtraction problems with a borrow operation and the working memory demands of a letter-recall task caused greater performance deficits in high math anxious participants compared to those with low anxiety, despite equal performance on non-borrow, low demand problems (Krause, Rudig, & Ashcraft, 2009).

Both global avoidance and local cognitive disruptions do well to explain the means by which math anxiety disrupts immediate performance and influences the development of math ability overall. However, there are components of the math anxiety and math ability relationship that are not explained well by the current frameworks. For one, the frameworks do not provide a plausible mechanism for the initial onset of math anxiety. The global approach suggests some first instance of anxiety, perhaps an embarrassing blackboard failure in front of the classroom. In contrast, the cognitive approach indicates that high math anxious students are possibly hindered by innate working memory inadequacies. There is current research to suggest that math anxiety begins in young children, primarily girls, when they model these attitudes from their female teachers and parents (Beilock, Gunderson, Ramirez, & Levine, 2010). However, there are some concerns with this explanation. First, this hypothesis seems to be incompatible with either of the previous approaches. Second, it appears to be incomplete in that it best explains the development of math anxiety in girls but lacks an equally strong explanation for math anxiety development in boys. The social-cognitive model of motivation can theoretically account for the development and onset of math anxiety. Instead of an initial apprehension of math, young children are apprehensive to display an inferior level of math intelligence that cannot be improved upon through effort. Therefore, instead of math anxiety, it may be more likely that teachers and parents are modeling fixed theories of math ability for young girls and boys (Gunderson, Ramirez, Levine, Beilock, 2012).

The global and local cognitive deficit theories are also insufficient in explaining how a student can be high math anxious and maintain optimal math performance (i.e., retain the effective problem-solving techniques and efficiently utilize cognitive resources). For example, Lyons and Beilock (2012) found cognitive-control aspects embedded within some participants with high math anxiety, such that these participants can prepare themselves to prevent anxiety from interfering with the cognitive processes necessary for completing an upcoming math task. The social-cognitive model of motivation states that a student can still have high ability; therefore, they may persist and approach a high self-efficacious task (i.e., a task they fell confident in completing). However, negative cognitions will still exist in the form of performance evaluation and the fear of possible failure (Beery, 1975). The model would predict that high ability and high math anxiety are more likely to be a result of entity theories of intelligence and performance-approach goals in academia. Also, negative thoughts do not need to be specific to the math task itself, but to the aspect of performance evaluation. Joormann, Levens, and Gotlib (2011) found evidence that the rumination of any type of emotional thought during a cognitively intense process may disrupt working memory resources. Persistent thoughts focused on performance goals and task avoidance, typical of entity theories of intelligence, may be a stronger indicator of debilitating math performance than math anxious thoughts in general.

The social-cognitive model of motivation would theorize that math anxiety manifests from entity theories of intelligence. In this case, students with an entity theory of intelligence would develop anxiety towards mathematics due to the negative social implications that failing a math task entails. Then, these implications would persistent in the form of ruminations that disrupt cognitive resources. These ruminations could consist of thoughts about negative performance evaluations and fears of failing. However, before these ideas can be tested, an empirical link must be made associating theories of intelligence with math anxiety, both in measures of attitude and in the online cognitive-deficits to working memory.

Stereotype Threat

Although the experiments in this thesis did not manipulate the construct of stereotype threat, I will briefly describe its impact on the social-cognitive model of motivation. Stereotype threat occurs when performance drops due to an experimenter characterizing a participant's ethnicity or gender negatively (Ashcraft & Rudig, 2012). For example, early research on this phenomenon found that mentioning a negative stereotype that African-American students usually perform worse on intelligence testing elicited drops in test performance, compared to another group of African-American students that were not given the negative stereotype (Steele & Aronson, 1995). The threat can work for practically any ethnic or gender group across a multitude of task domains (see Wheeler & Petty, 2001).

The cognitive mechanisms creating the drop in performance during a stereotype threat are similar to the cognitive mechanisms that link high math anxiety to worse performance, which was described earlier. Beilock, Rydell, and McConnell (2007) simultaneously manipulated stereotype threat and working memory demands using a modular arithmetic task. Females that were told that the study was examining why men are generally better than women at math had significantly lower accuracy than a control group. This effect was greatest in conditions of higher working memory demand: more difficult problems, horizontal orientations, and a secondary phonological load. A follow-up experiment found increased ruminations and negative thoughts during the stereotype threat. Women reported significantly fewer negative thoughts when the stereotype was not threatened. These results suggest that administering a negative stereotype elicits negative thoughts that compete for verbal working memory resources that are needed to effectively solve high demand math problems.

There is a method to neutralize the effect of the stereotype threat. Describing the effect of stereotype threat, before testing, cushioned participants from drops in performance (Johns, Schmader, & Martens, 2005). Participants were informed, “negative stereotypes… have nothing to do with your actual ability to do well on the test” (p. 176). These instructions are guiding participants to think incrementally about their ability, that test performance is no longer a measure of ability. This group had similar performance levels to a control group that was not given a stereotype threat. Another study also found that teaching malleable beliefs of intelligence significantly reduced the effects of stereotype threat in a sample of African-American students (Aronson, Fried, & Good, 2002).

If stereotype threat decreases the availability of cognitive resources and getting participants to think of ability as a malleable trait reduces this effect, then it suggests that participants that view test performance as measure of effort have fewer cognitive disruptions. Therefore, viewing test performance as a measure of either one’s own ability or the intellectual capabilities of a group, an entity belief of intelligence, may be behind these cognitively disruptive, negative ruminations. In fact, negative thoughts and ruminations during a stereotype threat were mostly focused on performance goals and comparing intellectual abilities between the stereotyped and control groups (e.g., math ability of men compared to women) (Beilock, Rydell, & McConnell, 2007). This formulation would also explain why having higher group-identification would increase the effect of the stereotype threat (Schmader, 2002); increased identification with the stereotyped group would increase the attribution transfer of explaining performance on personal effort to intellectual capabilities of the group.

As stated earlier, the experiments in this thesis did not directly manipulate or measure the effects of stereotype threat on entity vs. incremental beliefs of intelligence. However, the underlying mechanisms and ways to alleviate stereotype threat support a framework in which the social-cognitive model of motivation explains the connections among attitudes towards math, online cognitive-deficits during math, performance on a math task, and math achievement in academia.

Current Experiments

The proposed experiments tested the effectiveness of the social-cognitive model of motivation in predicting the study habits and math performance of college students when they are faced with a mathematical challenge. In Experiment 1, participants were introduced to modular arithmetic, a mathematics task that is unfamiliar to most undergraduate students. In an initial test, participants judged the bivalence (i.e., true vs. false) of a set of modular arithmetic statements. The key aspect of the initial test is that participants were not given the correct solution algorithm. After performance feedback on the initial test, participants had the option to study additional example modular arithmetic statements with answers so they could try to learn the correct algorithm and possibly improve their performance on a final test. The alternative option was to skip the studying session and continue immediately into the final test.

The main hypothesis of Experiment 1 was that participants who self-report having an entity theory of intelligence would choose to study less than participants who self report an incremental theory of intelligence. As hypothesized, participants' implicit theory of intelligence (i.e. the continuum of entity to incremental) would be a stronger predictor of total study time and the total number of example statements viewed than participants' level of math anxiety, math ability, belief about effort, academic goals, or response to academic failure, although these variables may significantly predict differences in studying. Because study habits would be different, implicit theories of intelligence would therefore strongly predict performance on a final testing session. More time spent studying would translate into participants with an incremental theory of their math intelligence having lower error rates and faster reaction times than participants with an entity theory. However, because predicted final test performance differences in students with separate theories of intelligence would be confounded by different amounts of studying, these hypotheses were not the focus of Experiment 1.

In Experiment 2, participants were taught the correct solution algorithm from the onset of the experiment and then given one test at the end, without a study session. Therefore performance differences on the test would no longer be confounded by differences in preferences to study. Characteristics of the modular arithmetic statement were varied, such as statement size, single vs. double-digit subtraction, and statement difficulty, subtraction with or without a borrow operation. More complex problems require more working memory resources, which would be reduced for participants with entity theories of intelligence. It was hypothesized that the largest performance differences between entity and incremental theorists would occur when statements are large and contain a borrow operation; slightly smaller when a statement is either large or contains a borrow operation, and smallest when statements are small and do not contain a borrow operation. Although studies have found evidence for speed-accuracy trade-offs in populations with high math anxiety, the results are often difficult to predict; a reason for this difficulty may involve interactions of math anxiety and other academic attitudes. Analyses of speed-accuracy tradeoffs for math anxiety or academic attitudes were purely exploratory.

Another hypothesis was that in both experiments, participants with entity theories of intelligence would place greater emphasis on ability and lower emphasis on effort when asked to complete the word equation, "Math intelligence = _____% effort + _____% ability." Participants with high math anxiety, negative beliefs about effort, and who respond helplessly to academic failures would also place greater emphasis on ability in the math intelligence equation. Academic goals and math ability would not predict different emphases on effort or ability; however, math ability may predict a participant's ability to generate two values that add to 100%.

CHAPTER 2

EXPERIMENT 1

Methods

Participants

Ninety-eight participants were recruited from the UNLV Subject Pool for partial completion of class credit. Three participants were excluded from analyses due to previous knowledge with modular arithmetic. Another three participants were removed because of computer errors and missing data. After exclusions, Experiment 1 consisted of 92 participants of which 48 were male and the mean age was 20.47 (*SD* = 4.396).

Materials

Participants completed an eighteen-item math demographics questionnaire to determine their age, gender, academic class, ethnicity, and math history. Items probing math history include grades and the number of completed courses in high school and college. The questionnaire also asked if participants have specifically completed algebra, trigonometry, geometry, calculus, or statistics.

To assess math ability, participants took a pencil-and-paper version of the arithmetic portion of the Wide Range Achievement Test – 3 (WRAT). The mathematics assessment is a timed twenty-minute test that contains 40 items. Statements ranged in difficulty from simple arithmetic to solving for unknowns in linear equations. Participants were given a point for every correct answer. Scores can range from 0 to 40.

The Abbreviated Math Anxiety Scale (AMAS) was used to determine participants' degree of math anxiety (Hopko, Mahadevan, Bare, & Hunt, 2003). The nine item AMAS has a participant rate on a five-point scale from 'not at all anxious' to 'highly anxious' the degree of anxiety in math related situations in either academic or natural settings. High scores on the AMAS characterize high math anxiety. Items rated as 'not at all anxious' are scored with 1 point; items rated as 'highly anxious' are scored with 5 points. Scores from the nine items are summed for a total math anxiety score. Scores on the AMAS can range from 9 to 45.

Participants also completed four measures assessing academic attitudes of the social-cognitive model of motivation. Each measure examines the major components of the model: theories of intelligence, goals in academia, beliefs about effort, and responding to failure. Every item in each measure was rated on a six-point scale (agree strongly - disagree strongly). Before each measure, the participant was told the general topic specific to that measure, that there were no right or wrong answers, and that we were interested in their opinions. Some of the wording was adapted from language designed for elementary school children into language better suited for a college adult population. For example, colloquial terms such as "a lot" were changed to "significantly" or "substantially".

The first measure determined a participant's implicit theory of intelligence. The eight items taken from Dweck (1999) dichotomized a participant into an entity or incremental theory of intelligence group. Four of the statements corresponded to the entity viewpoint (e.g., "Your intelligence is something about you that you can't change very much"). The remaining four items corresponded to incremental theory (e.g., "You can always substantially change how intelligent you are.”), and were reverse coded. Participants received a mean theory of intelligence score for the eight items with the lower scores (1) representing an entity theory and the higher scores (6) signifying an incremental theory of intelligence. Participants can be labeled as entity or incremental for group analyses by splitting scores at the middle of the spectrum (i.e., 3.5) or along a measure of central tendency (e.g., median).

The second measure, called academic goals, contained three portions with three items each (Mueller & Dweck, 1998). The first portion determined the degree to which the participant values performance as a means to demonstrate ability (e.g., “I like school work best when I can do it perfectly without any mistakes”), known as performance-approach goals. The second portion determined if participants view academic performance as a way to avoid demonstrating a lack of ability (e.g., “An important reason I do my schoolwork is so I won’t embarrass myself”), known as performance-avoidance goals. The final three items of the scale determined if a participant values schoolwork as an opportunity for learning (e.g., “I like school work that I’ll learn from even if I make a lot of mistakes”), known as learning goals. Each item was reverse coded such that higher scores indicate higher value for the particular goal being tested. Although each subtest is scored individually, the three subtests together gave an indication of a participant’s motivation to succeed in academia.

The third measure determined a participant’s beliefs about the effectiveness of effort in academia (Blackwell, Trzesniewski, & Dweck, 2007). The effort beliefs scale contains nine items, five items are negative and four are positive. Negative items measured a participant’s belief that effort does not lead to success and is an indicator of poor ability (e.g., "If you're not good at a subject, working hard won't make you good at it"). Positive items measured a participant's attitude that positive outcomes are attributed to effort (e.g., "The harder you work at something, the better you will be at it."). Positive items were reverse coded to create a scale of positive effort beliefs, such that low scores indicate a negative view of effort and a high score endorses a positive belief.

The fourth measure, created by Blackwell, Trzesniewski, and Dweck (2007), determined how a participant responds to academic failure. By reading a hypothetical scenario, participants were instructed to imagine that they had unexpectedly failed a quiz in a class. They were then asked to agree or disagree, using the previous six-point scale, on four attributions for that failure and five possible strategies in response to the failure. The four items of the attribution portion of the subtest are helpless oriented (e.g., "I'm just not good at this subject"). Participants were given a mean attribution score, on which low scores indicate helpless attributions and high scores indicate to mastery-oriented attributions failure. The five items of the strategies portion of the subtest include two items supporting positive strategies (e.g., "I would spend more time studying for tests") and three items endorsing negative responses to failure (e.g., "I would try not to take this subject again"). Positive items were reverse coded and combined with negative items to create a mean positive strategies score, such that high scores support responding positively to an academic failure.

Novel Math Task

Modular Arithmetic was the novel math task in this experiment. Modular arithmetic is a type of math statement using an algorithm of subtraction and division in a unique format. This type of math provides theoretical implications in advanced number theory and practical applications in encryption and code breaking. This topic is usually only taught at the highest levels of math education; therefore, few undergraduate students have been exposed to these types of statements. The modular arithmetic statements, $x \equiv y$ (mod z), are read as, "x is congruent to y modulo z." The statements are true if z divides (x – y) evenly. For example, 15 ≡ 9 (mod 3) is true because 15 – 9 = 6, and 6 is divisible by 3. By simple alterations, a true statement can be transformed into a false statement; for example, the earlier statement can be made false by changing the third number from a 3 to a 4 (i.e., 15 ≡ 9 (mod 4)). Thus, a verification task on modular arithmetic is effective in assessing math performance (i.e., reaction times and error rates). Modular arithmetic has been used in previous research to identify the needs of working memory in mathematics tasks within conditions of math anxiety, choking under pressure, and stereotype threat (Beilock & Carr, 2005; Beilock, Rydell, & McConnell, 2007; Krause, Rudig, & Ashcraft, 2010). In these studies, statements with numbers greater than 10 or required a borrow operation in the subtraction problem placed greater demands on working memory and therefore decrements in performance (i.e., increases in reaction time and error rates).

Modular arithmetic statements were selected based on three factors. Statements were evenly divided into true or false, borrow or non-borrow subtraction, and small or large statement size; statements are considered large when both the minuend and subtrahend are double digits. Between the two testing phases, there were 90 modular arithmetic statements. Each participant's initial testing phase contained the same ten statements and these statements were evenly divided between true and false. The final testing phase contained the same eighty statements for each participant, ten statements from each combination of the three factors. To insure that statements with similar numbers or responses were not presented consecutively, statement sets were counterbalanced in a predetermined random order.

Modular arithmetic statements in the study phase were different from test statements. Each participant saw the same study statements in the same predetermined order. The statements were ordered in a way that facilitated learning an effective procedure for solving modular arithmetic. Statements were shown with their true or false answers. Successive statements in the study session were altered by one of the digits slightly, which may or may not have changed the true or false value; therefore, guiding the participant towards a solution algorithm. Informal pilot testing demonstrated this to be an effective method.

Procedure

Math demographics, AMAS, academic attitude measures, and the novel math task were presented using E-Prime 2.0 experimental software (Psychology Software Tools, Inc., Schneider et al., 2002). Participants completed the informed consent first. The math demographics questionnaire, the AMAS, the WRAT, the academic attitudes and motivation measures were presented consecutively and counterbalanced across participants. However, because the AMAS is a five-point scale and the academic attitude measures are six-point scales, the WRAT-3 always interceded these two measurements. Presentation of each of the four measures of the academic attitudes was randomized, as well as item order within each measure. The novel math task was counterbalanced with the other block of materials (i.e., either immediately after the informed consent or as the last task of the experiment).

The novel math task consisted of three phases: initial test, study session, and a final test. Participants began with an initial testing phase with feedback that provided the participant with a benchmark of their ability on the modular arithmetic task. In the study session, participants were given the opportunity to view example modular arithmetic statements with answers so that they could learn an effective algorithm. The participants then applied what they had learned from the study session in a final testing phase.

To begin the novel math task, participants were introduced briefly to the concepts of modular arithmetic. They were shown the format of each statement, $x \equiv y \pmod{z}$, and told that statements are either true or false. Participants were informed that determining the validity of a statement is computed using simple math processes.

After the introduction, E-prime was used to asked participants if they had been exposed to modular arithmetic before. If participants answered “no”, then the experiment continued into the initial testing session. If the participant responded “yes”, a follow up question asked if they know the process to determine if a statement is true or false.

If a participant responded “no” to the follow up question, then the experiment continued into the initial testing session. If a participant instead answered “yes”, E-prime presented them with a text box where they could type in the method for determining the validity of a modular arithmetic statement. Participants that typed in the correct algorithm were allowed to finish the experiment; although, their data was removed from analysis. When the participant was finished typing, they began the initial testing session. An experimenter was present during this phase, but only to answer questions regarding the computer response buttons. The experimenters did not give clues, hints, or any indication to the participants about modular arithmetic and its correct algorithm.

Instructions for the initial testing phase informed participants to respond true or false with button presses ‘e’ and ‘i’. Equal emphasis was placed on both speed and accuracy. There were ten trials in the initial testing phase. Trials began with a 1500 ms ready prompt, followed by the presentation of the modular arithmetic statement. The statement was located on the upper portion of the screen, while underneath the statement was text reading “Please respond True (e) or False (i).” The statement was presented for twelve seconds or until participants made a response. After a response, the participant received immediate feedback on that trial. A correct response was followed by a slide containing a green square with the word “Correct!” typed within. An incorrect response was followed by a slide containing a red square with the word “Incorrect!” typed within. The feedback slide was followed by the ready prompt of the next trial. If participants did not respond within twelve seconds, a screen was presented stating “The modular arithmetic statement has timed-out. Please make your responses quicker.” for two seconds. Mean reaction times for solving modular arithmetic are about five seconds with over ninety percent of the data falling under twelve seconds (Krause, 2009). A limit of twelve seconds per statement was used to insure that participants remain engaged in the task. The cap also prohibits participants from spending time to adopt a solution algorithm during the initial test. Timed-out responses were not given immediate feedback, however were recorded as an incorrect response in the post-initial test feedback, as described in the next paragraph.

After completing the tenth trial, the participant was given an indication of their performance by the number of statements answered correctly, “You have seen 10 statements. You have answered __ correctly.” Participants were then given the option to skip or to proceed to the study session, where they could study example modular arithmetic statements that were provided with answers. These statements were shown one at a time in a predetermined order. The presentation order allowed participants to infer the mathematical algorithm that solves a modular arithmetic statement. A screen informed the participants that they could either study the example statements or continue to the final test of statements. This screen stated that example statements are designed to teach them how to solve modular arithmetic statements.

If a participant responded yes, they were shown another screen outlining the study session procedure. The participants were explicitly instructed to use the example statements as a guide to determine if a modular arithmetic statement is true or false. Additional instruction told the participants that at any time they may press ‘y’ to quit studying and continue to the final testing session. The example statements were shown one at a time, and participants were unable to go back to view previously seen example statements. Each example presented the modular arithmetic statement on the upper portion of the screen with the correct ‘True’ or ‘False’ designation directly underneath that. On the lower portion of each screen were instructions informing participants to press the ‘spacebar’ to see the next example or press ‘y’ to quit studying and continue to the final testing session. At no time were participants making ‘True’ or ‘False’ responses during the study session.

Although participants were told that they have a maximum of twenty minutes to study, there were also a maximum of thirty example statements. Participants were not informed of this maximum. If participants are told that there are thirty example statements, then they may feel pressured to study each one. When a participant reached the time limit or finished studying the last example statement, they were prompted to press ‘y’ to continue to the final testing session.

When participants were finished with the studying session, they saw a transition slide before continuing into the final testing session. Instructions reminded them to respond true or false with equal emphasis on speed and accuracy. Participants were also told to use what they learned from the example statements to help them solve the modular arithmetic. The presentation timing of trials in the final testing session was similar to the initial testing phase. The only difference was that in the final test participants were not given immediate feedback after a trial response. This was done to prevent any learning from occurring during this phase.

At the end of second testing session, participants received feedback on the number of correctly answered statements similar to what they saw after the initial testing session. After the final test feedback, E-prime prompted the participant to input numerical values that complete the following equation: Math intelligence = _____% effort + _____% ability. The experiment concluded with a debriefing explaining the ideas and hypotheses of the study. The experiment took approximately one hour to complete.

Results

Measures

Participants’ self-report data on the academic attitudes, math anxiety, and math ability measures were combined across both experiments to create between-subjects variables for all measures (see Table 1 for means, standard deviations, medians, and group sizes). Similar to what has been shown in past research, math anxiety was correlated negatively with math ability, $r = -.173$, $p < .01$ (see Table 2 for all correlations), with participants that reported lower ratings of math anxiety performing better on the WRAT. Math anxiety was positively correlated with performance goals, $r = -.143$, $p < .05$. Participants with higher ratings of math anxiety were more likely to adopt performance goals in academia. Likewise, participants who favored performance goals recorded lower math ability, $r = -.143$, $p < .05$.

Consistent with results of the social-cognitive model of motivation, higher scores on the implicit theories of intelligence belief (i.e., incremental) were positively correlated with adopting learning goals in academia, $r = .211$, positive beliefs about effort $r = .369$, and mastery responses to academic failure, $r = .332$, *p*s $< .01$. The strongest correlation among between subjects factors was between effort beliefs and attributions to failure $r = .505$, $p < .001$. Participants with positive beliefs about effort were significantly more likely to espouse hard work and doubling one's effort as appropriate responses to a scenario of academic failure. Additionally, both attributions to failure and effort beliefs were strongly correlated with learning goals, $r = .318$ and $r = .505$, *p*s $< .001$.

For the purposes of factorial analyses of variance, math anxiety was split into three groups; participants falling below half a standard deviation of the mean were labeled low math anxious, participants half a standard deviation above the mean are high math anxious, and participants scoring in between those values are medium math anxious. Implicit theories of intelligence, effort beliefs, responses to academic failure, and math ability were divided over the median into incremental and entity, low and high effort, helpless and mastery-oriented response to failure, and low and high math ability groups, respectively. In both experiments, less than 10% of participants favored performance-avoidance goals. The approach versus avoidance construct was therefore collapsed into performance goals.

Response Times and Error Rates from the Modular Arithmetic Tests

Response times and error rates were recorded during initial and final tests of modular arithmetic ability. Response times for incorrect responses were removed from analyses. As stated earlier, a 12 second cap was included as a precaution against outlying responses; therefore all responses made within the time limit were deemed acceptable and no outlier analyses were performed on response time data. Final test trials that timed out were scored as an error and the response time was removed from analysis.

In Experiment 1, 109 trials timed out. Trials with response times less than 250 ms were considered as anticipatory; response times and responses from these trials were removed from analyses; there were 10 of these trials in Experiment 1. In total, data from less than 1.6% of trials were removed from final test analyses due to timed out or anticipatory responses. The response times of 11 trials that timed out in the initial test of Experiment 1 were also removed from analysis.

Initial Test

Recall that in Experiment 1, participants solved an initial test of 10 modular arithmetic statements without knowledge of the correct procedure. The initial test was used to give the participants insight into their baseline abilities of this specific mathematics task. According to binomial distributions for 10 trials with 50% probability of answering correctly, participants with error rates between 30% and 70% fall within chance levels, $p > .10$. Mean response times per trial during the initial test were not significantly different among math anxiety groups, theories of intelligence, effort beliefs, attributions of failure, and math ability, *p*s > .10. However, participants with learning goals in academia spent significantly more time responding per statement (M = 4639 ms, SE = 267 ms) than participants with performance goals (M = 3866 ms, SE = 198 ms), $t(90) = -2.362$, $p < .02$. Participants with learning goals may have been attempting different solution strategies in an effort to learn the correct algorithm.

On the initial test, differences in error rates among low, medium, and high math anxiety groups were non-significant, $F < 1$; and all groups performed at chance levels (see Table 3 for means and standard errors of response times and error rates for math anxiety, academic attitudes, and math ability groups on the initial test). Difference in error rates between incremental and entity participants were non-significant, $t < 1$, and both groups performed at chance levels. There was no difference in error rates between participants with performance or learning goals, $t(90) = -1.719$, $p = .089$, and both groups of participants performed at chance levels. Participants with low effort beliefs had similar error rates to participants with high effort beliefs, $t < 1$, and both groups performed at chance levels. Difference in error rates between helpless oriented and mastery oriented participants were not significant, $t(90) = 1.866$, $p = .065$, and both groups performed at chance levels. There was no difference in error rates between participants with low math ability versus those with high math ability, $t < 1$, and both groups of participants performed at chance levels. Therefore, all groups performed at chance levels on the initial test and thus, appeared to be naïve to the correct method in solving modular arithmetic statements.

Study Session

Knowing their modular arithmetic abilities from their performance feedback on the initial test, participants were given the option to self-pace themselves through example modular arithmetic statements paired with the correct true or false answers. If participants chose to study, after every example they were given the option to quit studying and continue on to a final test. Studying behavior was measured using two dependent variables: the number of statements viewed and the total time spent studying statements.

The main hypothesis for this experiment stated that differences in academic attitudes would predict studying behavior. However, analyses confirm that there were no significant differences in studying behavior among the groups of academic attitudes. Participants with incremental and entity theories of intelligence studied a similar number of examples, $t < 1$, for a similar amount of time, $t < 1$, (see Table 4 for means and standard errors of study session behaviors for math anxiety, academic attitude, and math ability groups). There was a non-significant difference in number of examples studied and total studying time for participants with performance goals versus learning goals, ps > .10. Differences between low and high effort beliefs were also non-significant, ps > .10. Mastery oriented students studied the same number of statements for the same amount of time as helpless oriented students, ps > .10. Differences among math anxiety groups were also non-significant; low, medium, and high math anxious participants studied the same number of statements, $F < 1$, and studied for the same amount of time, $F < 1$.

However, there was a significant effect of math ability. Participants with high math ability studied more statements than participants with low math ability, $t(90) =$ -

2.820, $p < .01$. High math ability participants also studied for a longer amount of time, $t(90) = -2.356$, $p < .025$. Further analysis reveals that average time spent per statement was similar between math ability groups, $t < 1$; therefore, the significant difference in total time was a consequence of viewing more examples.

It was originally hypothesized that academic attitudes would lead to differences in studying behavior and therefore create differences in modular arithmetic ability. This confound would have impaired the interpretation of performance on the final set of 80 statements. Because studying behavior was similar among the different academic attitude and anxiety groups, analyses of the final test performance may yield some interesting results.

Final Test

Before turning to the analyses of the final test, it should be noted that fewer than one quarter of the participants in Experiment 1 were able to infer the correct solution algorithm for modular arithmetic. This analysis is discussed in further detail below; however, it appears that many participants developed heuristics in making true and false decisions during the final test. This pattern of responses created latency and error rate data that differed with the standard results found in the literature and also with the final test performance data in Experiment 2, where participants were explicitly taught the correct algorithm. The analyses are presented below for the sake of completeness but should be interpreted cautiously.

Analyses of the final test were conducted using six separate multivariate 2 x 2 x 2 within-subjects ANOVAs for each between-subjects factor: (1) math anxiety, (2) implicit theories of intelligence, (3) effort beliefs, (4) academic goals, (5) mastery vs. helpless responses to failure, and (6) math ability. Within-subjects factors were true versus false statements, small versus large statements, and statements with or without a borrow operation. Dependent variables were response times and error rates. All main effects and interactions not mentioned were insignificant at $p > .10$.

In all between-subjects analysis there was a significant three-way interaction among within-subjects variables true/false, statement size, and borrow for the dependent variable response times, $F(1, 89) = 4.881$, $p < .05$. Main effects of all three within-subjects variables contribute to the interaction in response times. Participants were slower to solve false statements than true statements, $F(1, 89) = 18.853$, $p < .01$ (see Figure 1). Large statements were solved slower than small statements, $F(1, 89) = 12.676$, $p < .01$. Statements with a borrow operation were solved slower than statements without a borrow, $F(1, 89) = 13.380$, $p < .01$. The main effects were consistent with past research on problem difficulty; however, details of the interactions revealed the inconsistencies. Simple effects analyses of the interactions indicate that in false conditions, response times between small and large statements were not significantly different from each other for both non-borrow and borrow; for true statements, small statements were significantly slower than large statements for only the no borrow condition. Subsequently, when statements were large, response times were significantly faster for non-borrow compared to borrow conditions in the true condition, yet non-borrow and borrow were not significantly different in small statements size and true condition nor were they significantly different for either scenarios in the false condition. Finally, in all statement size and borrow factorial combinations, false statements were always significantly slower than true statements; however the greatest disparity occurred for large statements with no borrow operation. Participants were on average 894 ms slower to correctly indicate false than to recognize the answer with a true response.

There was a significant interaction between true/false and borrow for error rates, $F(1, 89) = 7.018$, $p < .01$ (see Figure 2). Participants made more errors on true statements than false statements, $F(1, 89) = 89.086$, $p < .01$. Inconsistent with past research, participants made more errors on small statements than large statements, $F(1, 89) = 81.798$, $p < .01$; additionally, there was no main effect of borrow on error rates, $p > .10$. Analysis of simple effects suggests that participants had significantly higher error rates for non-borrow over borrow statements only in false statements; for true statements, differences in error rates between borrow and non-borrow were not significant.

Main effects and interaction involving the between-subjects variables implicit theories of intelligence, effort beliefs, and responses to failure were not significant, *p*s > .05. There was a significant interaction among math anxiety and statement size for error rates, $F(1,89) = 4.568$, $p < .025$ (see Figure 3). Consistent with past research, for small statements, low math anxious participants had significantly fewer errors than participants with high math anxiety, both groups were not significantly different than medium math anxious. Inconsistent with the literature, for large statements, all anxiety groups are statistically equal in their error rates. Despite the extra processing required, each level of math anxiety group significantly decreased their errors when answering large statements instead of small statements.

There was a significant main effect for the between-subjects variable academic goal for both response times and error rates, $F(1, 90) = 5.308$, $p < .025$, and $F(1, 90) =$

8.044, $p < .01$, respectively. Participants with learning goals spent significantly more time responding to statements and made fewer errors than participants with performance goals.

A significant interaction was revealed among academic goals and the three within-subjects variables for the dependent variable error rates $F(1, 90) = 4.752$, $p < .05$. Simple effects show that in the false condition, participants with performance goals committed significantly more errors than participants with learning goals only during small statements with no borrow operation. In the true conditions, participants with learning goals in every combination of statement size and borrow operation made significantly fewer errors than participants with performance goals.

For the dependent variable response time, there was a significant interaction among academic goals, true/false, and borrow variables, $F(1, 90) = 7.027$, $p < .01$ (see Figure 4). Simple effects indicate that participants with either type of academic goal significantly increased their response time from no borrow to borrow statements under the true condition but remained stable under the false condition. Additionally, in the false condition, participants with learning goals were slower to solve statements for both borrow conditions. For true statements, response times were statistically equivalent among academic goal groups for no borrow and only marginally different when a borrow operation was present. Consistent with the previous results, response time differences between false and true conditions were significant within each combination of statement size and borrow factors.

There was a significant main effect of math ability on error rates, $F(1, 90) = 17.128$, $p < .01$. Participants with low math ability produced significantly more errors ($M = .480$, $SE = .018$) than high math ability participants ($M = .368$, $SE = .020$). Significant two-way interactions were found with math ability and each of the within-subjects variables in response times, *ps* $< .05$ (see Figures 5-7). Low math ability participants were statistically equivalent in response times when solving statements of true versus false, small versus large, and non-borrow versus borrow. High math ability participants were significantly slower to solve statements when they were false, when they were larger, or when statements had a borrow operation. Participants with high math ability, having studied more example statements, were able to recognize more difficult statements and take extra time to insure the accuracy of their response.

Immediately after the final test, participants were asked to reflect upon the algorithm they used to solve the modular arithmetic statements. For example, one participant correctly stated, "If the difference of X-Y was divisible by Z the statement is true." Responses from other participants were clear indications that they did not learn the correct algorithm and merely adopted a simple heuristic, "If the numbers had anything in common" and "I attempted to multiply the numbers, but that did not seem to work. The experiment was confusing. I am terrible at math." Analyzing the comments, it was determined that 22 (23.9%) of the participants were able to infer the correct algorithm from the study session. Recall that participants were screened beforehand for knowledge of modular arithmetic, and participants that correctly learned the algorithm had claimed to not have seen it before. However, independent samples t-test revealed that those who learned the algorithm made significantly fewer errors ($M = .336$, $SE = .040$) during the initial test than participants that did not learn ($M = .463$, $SE = .021$), $t(90) = 2.927$, $p < .005$. Yet, the binomial probability states that 66.4% accuracy is within chance levels for only 10 trials with 50% probability.

Participants that learned the algorithm were similar in math anxiety, theories of intelligence, academic goals, effort beliefs, and responses to failure to participants that did not, *p*s > .10. Participants that learned the algorithm scored significantly higher (*M* = 33.6, *SE* = 0.79) on the WRAT than participants that either guessed or used a simpler heuristic (*M* = 29.0, *SE* = 0.55), $t(90) = -4.248$, $p < .001$. After controlling for math ability, participants with algorithms were not significantly different than their counterparts using heuristics in the number of examples studied or time spent studying during the study session, *p*s > .10.

It is not surprising that participants with algorithms make fewer errors than participants with heuristics, $F(1,89) = 110.475$, $p < .001$. However, a significant interaction with true/false indicates that participants with heuristics made significantly more errors for true statements (*M* = .669, *SE* = .022) than false statements (*M* = .300, *SE* = .018); participants with algorithms made statistically equivalent errors for true (*M* = .299, *SE* = .041) and false statements (*M* = .217, *SE* = .034). The heuristics that participants adopted from studying led them to make false responses more consistently, and therefore perform worse than chance for true statements. Participants with heuristics responded false on average 68.4% of all trials while participants with algorithms responded false significantly less at 55.3% of all trials, $t(90) = 3.751$, $p < .001$.

Consistent with these findings, an interaction of statement size, borrow, and figuring out modular arithmetic was found for response times, $F(1,89) = 6.414$, $p < .025$. Participants using algorithms took longer to solve statements than participants using heuristics, significantly for small-borrow and large-no borrow statements (see Figure 8). Additionally, when participants use an algorithm, smaller statements are easier to solve than large statements; participants with heuristics were marginally slower when solving smaller statements than larger statements, $p = .051$.

Recall of Initial Test Performance

After participants received feedback on their performance on the final test, they were asked to recall their performance on the initial test. They were instructed to type the number of statements answered correctly. It was predicted that participants with more negative affect, maladaptive academic attitudes, and low math ability would underestimate their performance. Only 14% of participants incorrectly recalled their performance on the initial test. A difference score was created between the recollection of initial test performance and actual performance. Participants with a negative difference score underestimated their performance. Analyses determined that there were no significant differences among math anxiety, academic attitudes, or math ability groups, *p*s > .10 (see Table 5 for means and standard errors).

Math Equations

At the end of the modular arithmetic task, participants were asked to complete a word equation by formulating the contributions that effort and ability play into math intelligence. Eighteen participants were excluded from these analyses because their totals did not equal 100%. To examine whether these 18 participants were different than the other participants, comparisons were conducted. Participants that correctly summed to 100% were not significantly different than participants who did not sum to 100% in math anxiety, academic attitudes or math ability, *p*s > .10. Among all participants, there was a main effect of math equation weightings; participants thought that effort ($M = 57.2\%$, *SE*

= 2.15) significantly contributes more to math intelligence than ability (*M* = 42.8%, *SE* = 2.15), $t(73) = -3.322$, $p < .01$.

There was a significant interaction between math anxiety and the equation component weightings, $F(2,71) = 4.276$, $p < .019$ (see Figure 9). Simple effects revealed that participants with low math anxiety placed significantly more contribution of effort into math intelligence and less contribution of ability than high math anxious participants; the weighting from medium math anxious were not significantly different than either the low or high math anxious (see Table 6 for means and standard errors). Weights of effort and ability contributions were only significantly different from each other among low math anxious participants, $F(1, 71) = 18.112$, $p < .01$; effort was significantly greater than 50%; conversely, ability was significantly less than 50%.

In contrast to what was hypothesized, the math intelligence equation and incremental theory of intelligence interaction was not significant, $F(1,72) = 2.380$, $p = .127$. The same interaction with academic goals was also not significant, $F < 1$. Similarly, interactions with effort beliefs were not significant, $F(1,72) = 1.322$, $p = .254$. There was a marginally significant interaction between equation weightings and attribution, $F(1,72) = 3.097$, $p = .083$. Participants with mastery responses to failure placed greater emphasis on effort in contributing to math intelligence than participants with helpless responses. Mastery-oriented students' weightings of effort and ability were significantly different from each other, $F(1,72) = 14.047$, $p < .01$; helpless-oriented students did not place significantly different weights on effort or ability, $F < 1$. Participants with different math abilities placed similar emphasis on effort and ability, $F(1,72) = 1.399$, $p = .241$. Despite the non-significant interactions, it is interesting to note that one-sample *t*-tests on effort weightings reveal that the groups entity theorists, learning goals, high effort beliefs, and high math ability all placed significantly greater emphasis on effort in contributing to math intelligence, *p*s $< .01$.

Gender and Task Order

Effects related to gender were not originally hypothesized in the proposal. Differences in male and female math performance are negligible despite differences in attitudes towards math (Else-Quest, Hyde, & Linn, 2010). However, recent research found subtle differences in the reporting of math anxiety between males and females in a college sample dependent on the order of the task and measurement of math anxiety (Goetz, Bieg, Lüdtke, Pekrun, & Hall, 2013). Females' assessments of attitudes about math before testing or learning tasks are significantly greater than their reports of the same attitudes during or after the task. After a math task, reports on attitudes reflect experiential information; however, before a math task, self-reports reflect multiple semantic and conceptual beliefs, which in the case of females likely encompass biases about females' inferiority in mathematics (Hartley & Sutton, 2013; Robinson & Clore, 2002). To examine this confound, analyses below involve exploring interactions of gender and task order with math anxiety, academic attitudes, math ability, and learning modular arithmetic.

Recall that Experiment 1 consisted of 48 males and 44 females. Task order was evenly split among the participants; 46 participants completed the attitude and ability measures before the modular arithmetic task; 46 participants performed the modular arithmetic task before filling out attitude measures and completing the WRAT. A non-significant chi-square analysis revealed similar distributions of gender by task order in Experiment 1, $p > .10$.

Measures

Gender and task order effects were analyzed in separate 2 x 2 between-subjects ANOVAs for math anxiety, academic attitudes, and math ability. Between-subjects factors were male or female gender and task-first or measures-first task order. Dependent measure for math anxiety was total score on the AMAS. Average score per item on the implicit theories of intelligence, effort beliefs, and attribution to failure scales were used as dependent variables. Total score on the WRAT was treated as a dependent variable for math ability.

There was a main effect of gender on math anxiety, $F(1, 88) = 7.548$, $p < .001$. Females reported higher ratings of math anxiety ($M = 24.9$, $SE = 0.94$) than males ($M = 21.4$, $SE = 0.90$). The gender by task order interaction and the main effect of task order were not significant, *p*s > .05. Learning a novel math task had no effect on subsequent ratings of math anxiety and neither was this effect moderated by gender.

Interactions and main effects of gender or task order were not significant for implicit theories of intelligence, effort beliefs, and attributions to failure, *p*s > .05. Chi-square analysis of gender on academic goals was significant, $\chi^2(1, N = 92) = 5.420$, $p < .025$. Males were more likely to adopt learning goals over performance goals, 28 and 20, respectively; females were less likely to favor learning goals over performance in academia, 15 and 29, respectively. Task order had no significant effect on academic goals, $\chi^2 < 1$.

Gender and task order interacted significantly in measuring math ability, $F(1, 88) = 5.114$, $p < .05$. Simple effects analyses revealed that males and females performed similarly on the WRAT before engaging in the novel math task, $F < 1$ (see Figure 10). After the novel math task, females scored significantly worse than males, $F(1, 88) = 9.200$, $p < .005$, and significantly worse than females that took the WRAT before the task, $F(1, 88) = 5.969$, $p < .025$. Additionally, males performed similarly on the WRAT, regardless of its presentation order, $F < 1$.

Initial Test

The interaction of gender and task order and the main effects on error rates during the initial test were non-significant, *p*s > .10. Additionally, both males and females performed at chance levels; and task-first and measures-first groups also performed at chance levels. Interactions and main effects were non-significant for response times as well, *F*s < 1. Males and females entered the experiment naïve to modular arithmetic. Similarly, completing the measures first did not provide an advantage to understanding the modular arithmetic task.

Study Session

Previous analyses on studying behavior found significant main effects of math ability. Total score on the WRAT was added as a covariate to remove the influence of math ability to subsequent analyses of studying behavior. Gender and task order effects were analyzed first together in a 2 x 2 between-subjects multivariate ANOVA for time spent studying and number of example statements viewed. The interaction and main effects were non-significant, *p*s > .10. Further analyses of studying behavior explored gender and task order effects separately with math anxiety and each of the academic attitudes.

The interaction of gender and implicit theory of intelligence was significant for number of example statements studied, $F(1, 87) = 4.354$, $p < .05$, and marginally significant for time spent studying, $F(1, 87) = 3.206$, $p = .077$. Among entity theorists, females studied significantly more statements than males, $F(1, 87) = 3.984$, $p < .05$ (see Figure 11). Incremental theorist males and females studied a similar number of statements. Among males, incremental theorists studied more statements than entity theorists; females studied the same regardless of implicit theory of intelligence. The interaction of total study time was marginally significant because of a crossover effect. Males with incremental theories and entity theorist females were statistically equivalent and studied longer than entity theorist males and females with incremental theories, which were themselves statistically equivalent in study time (see Figure 12). Interactions and main effects of gender with math anxiety, academic goals, effort beliefs, and attributions to failure were non-significant, *p*s > .10 (see Table 7 for means and standard errors).

There were no significant interactions of task order with math anxiety or any of the academic attitudes, *p*s > .10 (see Table 8 for means and standard errors).

Final Test

Gender and task order were added as between-subjects factors in each of the six previous multivariate 2 x 2 x 2 within-subjects ANOVAs. Within-subjects factors included true versus false statements, small versus large statements, and statements with or without a borrow operation. Dependent variables were response times and error rates.

Average ratings on the implicit theories of intelligence measures were first considered as a covariate because of their interaction with gender during the study session; however, including the covariate did not significantly change the following statistics. The covariate was removed to maintain consistency with analyses performed earlier.

There was a significant four way interaction among gender, true/false, statement size, and borrow for the dependent variable error rates, $F(1,90) = 7.600$, $p < .01$. This interaction was supplemented by a marginally significant interaction between gender and statement size, $F(1,90) = 2.965$, $p = .089$, and a significant main effect of gender, $F(1,90) = 16.295$, $p < .001$. Females ($M = .487$, $SE = .020$) committed more errors than males ($M = .378$, $SE = .019$). The main effect of statement size discussed earlier, in which more errors occurred for small statements, affected the females more than the males. Error rates for females increased by 11.5% from large to small statements, males increased error rates by a smaller 7.8% (see Figure 13). The four-way interaction occurred because females and males were not significantly different in error rates when statements were false, large, and non-borrow (see Figure 14). In every other instance males outperformed females; and for true, small, borrow statements specifically there was a 19.5% difference in error rates between genders (see Figure 15). Additionally, there was only one occurrence of small and large statements being statistically equivalent, this occurred for males during true statements with a borrow. Finally, non-borrow and borrow were not significantly different in all but two instances: false condition and when either males solved large statements or females solved small statements.

The variables gender, statement size, and borrow created a three-way interaction in response times, $F(1,90) = 5.796$, $p < .025$. Female performance during small statements with a borrow was generating the effect. At this point only, female response time is significantly different than males, small statements are significantly different than large, and when no borrow is statistically equivalent to a borrow condition (see Figure 16).

Gender was combined with each of the other between-subjects factors in separate ANOVAs. Only math ability significantly interacted with gender for the dependent variable error rates, $F(1,88) = 8.759$, $p < .005$, (see Figure 17). Simple effects analyses reveal that high math ability males were significantly more accurate than females, $F(1,88) = 23.942$, $p < .001$, and significantly more accurate than low math ability males, $F(1,88) = 25.518$, $p < .001$. Low and high math ability females did not differ in error rates, $p > .10$.

Main effects and interactions of task order with gender, within-subjects factors, and with attitudes-related between-subjects factors were non-significant, *p*s > .10.

Participants that correctly typed in the correct modular arithmetic algorithm after completing the final test were significantly more likely to be male, $\chi^2(1) = 10.183$, $p < .001$. Given that math ability is related to both gender and learning the algorithm in this experiment, math ability may be confounding the relationship between gender and learning the correct solution algorithm. Task order was not significantly related to discovering the correct solution, $\chi^2(1) = .239$, $p > .10$.

Recall of Initial Test Performance

No gender or task order analyses were conducted due to the high percentage of participants (86%) that correctly recalled their performance on the initial test.

Math Equations

The three-way interaction among gender, task order, and equation component weightings was marginally significant, $F(1,70) = 3.180$, $p = .076$. Males that completed the task first gave significantly different ratings than males who took the measures first, $F(1,70) = 6.870$, $p < .025$, and marginally different than females that completed the task first, $F(1,70) = 3.317$, $p = .073$ (see Figure 18). One-sample t-tests revealed that task-first males were the only group who placed similar emphasis on ability and effort, $t(21) = 0.314$, $p > .10$. Males that completed the measures first and females, regardless of task order, placed significantly more emphasis on effort, *p*s < .05.

The same marginal effect was represented by replacing the variable task order with the between-subjects factor of attribution to failure, $F(1,70) = 2.873$, $p = .095$. Males with helpless responses to failure gave significantly different ratings than males with mastery responses, $F(1,70) = 6.771$, $p < .025$, and significantly different than females with helpless responses, $F(1,70) = 4.435$, $p < .041$. One-sample *t*-tests revealed that only helpless-oriented males placed similar emphasis on ability and effort, $t(11) = 1.096$, $p > .10$ (see Figure 19). Males and females with mastery-responses emphasized effort significantly more than ability, *p*s < .01. Females with helpless orientations differed in their percentage weightings only marginally, $t(14) = 1.888$, $p = .080$. All other effects of gender or task order with math anxiety, academic attitudes, or math ability were non-significant, *p*s > .10.

Discussion

The results of Experiment 1 did not fully support the proposed hypotheses. Mainly, participants' incremental or entity theories of intelligence did not elicit different patterns of studying behavior in learning a new mathematics task. Other academic attitudes of the social-cognitive model of motivation, such as academic goals, beliefs about effort, and attributions to failure were also not influential in how many example statements or for how long participants studied.

However, there were two important results regarding studying behavior. First, participants with higher math ability studied more example statements. Consequently, these participants were more likely to determine the correct modular arithmetic algorithm and have significantly better performance on the final test. Participants with high math ability likely recognized either their lack in understanding modular arithmetic or that studying more examples would lead to determining the correct method for solving modular arithmetic in a final test. Consequently, participants who were better at math performed better on the final test and were more likely to report the correct solution algorithm after the final test. Studying five statements on average more than low math ability participants presumably led high math ability participants to infer the correct algorithm. Furthermore, having better math ability and therefore greater knowledge of mathematics may have provided them with additional conceptual tools on which to build an inference.

The second important result was that studying behavior was moderated by gender. Consistent with the main hypothesis, males who believed that intelligence comes from effort studied more example statements and spent more time studying than males that viewed intelligence more as a fixed trait. After failing an initial test in modular arithmetic, incrementally oriented males sought to increase their modular arithmetic abilities by exerting more effort in the study session. However, females with theories closer to the entity spectrum studied more than females with incremental theories. These results tentatively support the secondary goal of this study, establishing the social-cognitive model of motivation as the framework for how negative attitudes about math develop and influence cognitive processes in mathematics. In accordance with stereotype threat literature, females with entity theories of intelligence and high abilities may have felt motivated to disconfirm the stereotype regarding their gender's abilities in math and therefore engaged themselves more in the task to showcase their fixed high ability during the final test (Mendoza-Denton, Kahn, & Chan, 2008). Although power was too low to reach significance, of the entity theorists, females with high math ability studied on average 7 more examples and for approximately 50% longer than females with low math ability. Only the females that were confident in their superior, fixed math ability were motivated to study as a preemptive measure against failure in a domain that may personify their self-worth (Dweck, 1999). The relationship between the social-cognitive model of motivation and stereotype threat will be discussed in greater detail in the general discussion.

More evidence of stereotype threat was found in the measures of math ability taken before or after the modular arithmetic task. Before participants were aware that they would be learning a new math task, females and males scored similarly. Their scores were also consistent with average math ability measurements from previous studies (Krause, Rudig, Ashcraft, 2009; Steiner & Ashcraft, 2012). However, if females took the math ability measure after learning the novel task, their scores significantly decreased, whereas scores of males were identical to their measures-first counterparts. For females, learning a difficult new math task through failing and self-study may elicit attitudes consistent with stereotype threat.

Males and females also differed in their attitudes within the social-cognitive model of motivation. Females were more likely to adopt performance goals over learning in academia and reported higher ratings of math anxiety compared to males. Females are at greater risk of adopting performance goals in academia because they are more likely to receive praise on their abilities and intelligence instead of demonstrations of effort (Dweck, 1999; Gunderson et al., 2013; Mueller & Dweck, 1998). Furthermore, consistent with the relationship proposed in this study, thoughts and rumination focused on displaying high performance should relate to higher anxiety.

This experiment is one of the first to show a relationship between math anxiety and the social-cognitive model of motivation. Participants that reported anxiety towards math evaluation and learning math reported academic attitudes that originate from a fixed view of intelligence. They were more likely to pursue performance goals, view effort as an indication of low intelligence, and attribute failure to low intelligence. These participants were also likely to align with entity beliefs in how they assigned the contributions of ability and effort in math intelligence (Dweck, 1999).

Hypotheses concerning the final test were tentative based on the assumption that there would be more substantial differences in studying behavior. However, studying across groups was mostly equivalent. Despite the amount of studying, a majority of the participants did not infer the correct solution and resorted to heuristics when making true and false decisions during the final test. Consequently, these participants responded false for a majority of trials. For example, one participant responded true only three times out of the eighty trials; twice when y * z = x (the only occurrences of this type of combination) and then once when y + z = x (one of three occurrences of this type of statement). This simple heuristic and others similar to it led participants to make rapid responses of false during small statements, therefore causing more errors when statements were true and coincidentally faster responses when statements were correctly false. The heuristic responses are responsible for the final test results being inconsistent with the math cognition literature. Mainly, increasing problem difficulty did not disrupt performance when cognitive resources were limited by math anxiety or entity related theories of the social-cognitive model of motivation.

Although the main hypothesis was not fully supported, Experiment 1 provides some of the first evidence that males' approach to learning mathematics was influenced by their implicit theory of intelligence and that math anxiety is also related to those beliefs. Furthermore, females' performance and behavior were influenced by an effect similar to a stereotype threat. Recall, it is theorized that the cognitive disruptions that impair performance in cases of anxiety and stereotype threat are attitudes from the social-cognitive model of motivation. Specifically, the ruminations consuming mental resources are related to how task performance reflects on the individual's intelligence, how the amount of effort exerted reflects on the individual's capabilities, and how failure will be attributed to oneself and the ramifications that follow failure. The concurrence of stereotype threat, math anxiety, and the social-cognitive model of motivation during a difficult math-learning task suggests some shared cognitive effects. Experiment 2 was designed to reveal the online cognitive effects of the entity related attitudes of the model.

CHAPTER 3

EXPERIMENT 2

Experiment 2 was included to address the potential that variations of studying could have on final test performance. When participants are allowed to control their engagement in studying a novel mathematics task, it makes performance analyses on the final test impractical. It cannot be known for sure if performance differences are due to theories of intelligence or because of varied amounts of studying. This impracticality is especially the case when the predicted group differences in final test performance mirror the predicted group differences in studying (i.e., incremental theorists studying longer and therefore having better performance on final test). Furthermore, the aim of this thesis to legitimize the social-cognitive model of motivation as an integral non-cognitive factor in mathematics cognition research relies on results demonstrating differences in final test performance, more specifically, interactions between attitude and the demands placed on immediate cognitive processes.

Experiment 2 introduced and taught participants how to solve modular arithmetic statements, followed by a test of that knowledge. With this procedure, differences in performance between participants with entity or incremental theories of intelligence are less confounded by their differences in motivation and study habits. The procedure teaching the participants how to correctly determine if modular arithmetic statements are true or false was quick and simple compared to the initial and studying phases of Experiment 1, again insuring that each participant would begin the final testing phase with the same knowledge. Explicit instruction in Experiment 2 should also counteract the confound of participants relying on heuristics to make their decisions that led to inconsistent results in Experiment 1.

Compared to participants with incremental theories of intelligence, it was hypothesized that participants with entity theories of intelligence would have slower latencies and make more errors in solving modular arithmetic statements that place greater demands on working memory resources (i.e., larger statement sizes and carrying operations). Differences in latencies and error rates between entity and incremental theorists were predicted to be non-significant for small statements and for statements without carry operations.

Methods

Participants

One hundred and thirty-six participants were recruited from the UNLV Subject Pool for partial completion of class credit. Three participants were excluded from analyses due to previous knowledge with modular arithmetic. Another three participants were removed because of computer errors and missing data. After exclusions, Experiment 2 had 130 participants of which 63 were male and the mean age was 20.50 (*SD* = 4.824).

Materials

Scales and achievement tests administered in Experiment 2 were identical to those used in Experiment 1. Participants completed a short demographics questionnaire and the AMAS for math anxiety. Math ability was determined from the WRAT. Academic attitudes were assessed using the implicit theory of intelligence measure, academic goals measure, effort beliefs measure, and the responses to academic failure measure. Coding and scoring of math anxiety, math ability, and academic attitudes parallel the previous study.

Novel Math Task

Modular arithmetic was the novel math task in Experiment 2. The statements used in this experiment were identical to the statements seen by participants in the final test of Experiment 1. Also, presentation order of the modular arithmetic statements was identical to the order presented in Experiment 1.

As a reminder, modular arithmetic statements were selected based on three factors. Statements were evenly divided into true or false, borrow or non-borrow subtraction, and small or large statement size (i.e., single or double digits). Each participant saw ten statements from each combination of the three factors. To insure that statements with similar numbers or responses were not presented consecutively, statement sets were counterbalanced in a predetermined random ordered.

Procedure

Math demographics, AMAS, academic attitude measures, and the novel math task were presented using E-Prime 2.0 experimental software (Psychology Software Tools, Inc., Schneider et al., 2002). Presentation of the informed consent was first. The math demographics questionnaire, the AMAS, the WRAT, the academic attitudes and motivation measures were presented consecutively and counterbalanced across participants. However, because the AMAS is a five-point scale and the academic attitude measures are six-point scales, the WRAT-3 always interceded the two measurements. Presentation of each of the four academic attitude measures was randomized, as well as item order within each measure. The novel math task was counterbalanced with the other block of materials (i.e., either immediately after the informed consent or at the end of the experiment).

The novel math task included two phases: example and test phases. The example phase introduced modular arithmetic and the correct algorithm for determining if a statement is true or false. The test phase was then administered to test performance differences between entity and incremental theorists.

The example phase began with a brief explanation of modular arithmetic. Participants were shown the format of each statement, $x \equiv y \pmod{z}$, and told that statements are either true or false. Participants were told that determining the validity of a statement is computed using simple math processes. This slide was identical to the one shown to participants in Experiment 1.

Following this introduction, E-prime was used to ask the participant if they had been exposed to modular arithmetic before. If the participant answered "no", then the experiment continued to the example phase. If the participant responded "yes", a follow up question asked if they knew the process to determine if a statement is true or false. If a participant responded "no" to the follow up question, then the experiment continued to the example phase. If a participant instead answered "yes", E-prime presented them with a text box where they could type in the method for determining the validity of a modular arithmetic statement. Participants that typed in the correct algorithm were allowed to finish the experiment; although, their data was removed from analysis. When the participant was finished typing, the experiment continue to the example phase.

All participants, even the participants that correctly gave the algorithm, were shown four examples that outline the methods and steps used to determine the validity of a modular arithmetic statement. The first three examples were statements with numeric values, the fourth statement was a general example using x, y, and z. Participants self-paced themselves through the example statements. An experimenter was present during this phase, but only to answer questions regarding the use of E-prime. The experimenters did not give clues, hints, or any indications to the participants about modular arithmetic.

After the example phase was complete, participants saw a transition screen instructing them to use the algorithm they just learned to solve a final set of modular arithmetic statements. This slide also provided directions for responding true or false. Participants responded true or false with button presses ‘e’ and ‘i’, respectively. Equal emphasis was placed on both speed and accuracy.

Presentation of the statements in Experiment 2 was identical to the presentation used in Experiment 1. Trials began with a 1500 ms ready prompt, followed by the presentation of the modular arithmetic statement. On the upper portion of the screen was the statement. Underneath the statement was text reading “Please respond True (e) or False (i).” The statement was presented for twelve seconds or until a response was made by the participant. After a response, the participant began the next trial. If participants did not respond within twelve seconds, a screen was presented stating “The modular arithmetic statement has timed-out. Please make your responses quicker.” for two seconds. Participants did not receive immediate correct or incorrect feedback after a response to prevent learning during the test phase and to make the task similar to the final test shown in Experiment 1.

Participants saw 80 modular arithmetic statements. After presentation of the eightieth trial, participants were prompted to rate their confidence in their performance on the final test on a scale from 0 to 8, where 0 is 'very poorly' and 8 is 'very well'. This rating assessed the participants' self-efficacy in modular arithmetic. Participants then received feedback on the number of statements answered correctly on the final test, "You have seen 80 statements. You have answered __ correctly." After the feedback, participants were instructed to rate how "pleased" they were with their performance on a scale from 0 to 8, where 0 is 'very unhappy' and 8 is 'very pleased'. This rating assessed the participants' self-concept in modular arithmetic. E-prime then prompted participants to input numerical values that complete the following equation: Math intelligence = _____% effort + _____% ability. The experiment concluded with a debriefing explaining the ideas and hypotheses of the study. The experiment took approximately one hour to complete.

Results

Response Times and Error Rates from the Modular Arithmetic Tests

Response times and error rates were recorded during the final test of modular arithmetic ability. Response times for incorrect responses were removed from analyses. One participant responded incorrectly on all trials in one of the within-subjects conditions, the empty cell of the analysis of variance was replaced with the mean response time of the same math anxiety group.

Similar to Experiment 1, because there was a 12 second cap on solving modular arithmetic statements, no outlier analyses were performed on response time data. Final test trials that timed out were scored as an error and the response time was removed from analysis. In Experiment 2, 381 trials timed out. Trials with response times less than 250 ms were considered as anticipatory; response times and responses from these trials were removed from analyses; there were 7 of these trials in Experiment 2. In total, less than 3.6% of trials were removed from analyses.

Training

The original hypothesis of Experiment 1 predicted significant differences in studying behavior among academic attitude groups. These predicted differences would then have confounded the ability to find the cognitive effects that academic attitudes, math anxiety, and math ability have on modular arithmetic performance. Experiment 2 was designed to train participants on the correct solution algorithm for modular arithmetic such that conclusions could be made about the effects attitudes have on the cognitive processes required to solve modular arithmetic.

In the training session, participants self-paced through four step-by-step examples on how to solve modular arithmetic statements. The first three examples were specific numerical statements followed by a general example with x, y, and z. Participants on average studied the examples for 97.5 seconds (*SD* = 35.8). Analyses of time spent studying the examples revealed no significant differences among math anxiety groups, between academic attitudes, or between math ability groups, *p*s > .05. Participants were therefore entering the final test with similar abilities in solving modular arithmetic statements.

Final Test

Analyses of the final test in Experiment 2 were identical to Experiment 1. Analyses of the final test were conducted using six separate multivariate 2 x 2 x 2 within-subjects ANOVAs for each between-subjects factor: math anxiety, implicit theories of intelligence, effort beliefs, academic goals, mastery vs. helpless responses to failure, and math ability. Within-subjects factors were true versus false statements, small verse large statements, and statements with or without a borrow operation. Dependent variables were response times and error rates. All main effects and interactions not mentioned were not significant at $p > .10$.

Replicating results in Experiment 1, there was a significant three-way interaction among within-subjects variables true/false, statement size, and borrow for the dependent variable response times, $F(1, 127) = 10.417$, $p < .01$. Main effects of all three within-variables supplement the interaction in response times. Participants were slower to solve false statements than true statements, $F(1, 127) = 103.053$, $p < .001$. Large statements were solved slower than small statements, $F(1, 127) = 638.896$, $p < .001$. Statements with a borrow operation were solved slower than statements without a borrow, $F(1, 127) = 469.416$, $p < .001$. The interaction was driven by smaller yet still significant differences among large and small statements that include a borrow operation in the true condition (see Figure 20). There was a significant interaction between statement size and borrow for error rates, $F(1, 127) = 7.731$, $p < .01$ (see Figure 21). Participants produced more errors on large statements than small statements, $F(1, 127) = 63.233$, $p < .001$; participants also made more errors on statements requiring a borrow operation, $F(1, 127) = 129.914$, $p < .001$. Consistent with the literature, the significant interaction was driven by a greater occurrence of errors when statements were both large and contained a borrow operation.

There were no main effects on both dependent variables for the between-subjects variables math anxiety, implicit theories of intelligence, academic goals, and mastery versus helpless responses to failure, *p*s > .05. There was a significant main effect of math ability on error rates, $F(1, 128)= 36.483$, $p < .01$; participants with lower math ability made more errors ($M = .202$, $SE = .012$) than participants with high math ability ($M = .098$, $SE = .012$). There was also a marginally significant main effect of response time for math ability, $F(1, 128)= 2.920$, $p = .090$. Low math ability participants were approximately 300 ms slower to solve modular arithmetic statements than high math ability participants (M = 4693 ms, SE = 130 ms).

There was only one significant interaction involving a between-subjects variable; for error rates, effort beliefs of participants interacted with borrow, $F(1, 128) = 4.913$, $p < .028$. Simple effects analyses indicated that there was no significant difference between participants with positive or negative beliefs about effort, regardless of the presence of a borrow operation. However, participants with positive effort beliefs suffered from a larger increase in errors when comparing non-borrow statements to statements with a borrow operation, an increase in error of 12.2%. Participants with negative effort beliefs increased their errors by a smaller 8.2% when comparing non-borrow statements to statements with a borrow operation.

Self-efficacy and Self-concept

To assess the participants' self-efficacy for modular arithmetic, immediately after solving the last statement in the final test, participants were prompted to rate their confidence in their performance on a scale from 0 to 8. They were then given feedback on how many trials they answered correctly out of 80. To assess math self-concept, the participants were then instructed to rate how "pleased" they were with their performance on a scale from 0 to 8. Ratings of self-efficacy were significantly correlated with final test accuracy, $r = .611$, $p < .001$, and self-concept, $r = .451$, $p < .001$. Similarly, self-concept correlated significantly with final test accuracy, $r = .447$, $p < .001$. Although significant, these correlations appear low considering the proximal time of the ratings and presentation of final test performance. Math anxiety, academic attitudes, or math ability may be influencing participants' confidence in predicting their performance or assessment of their abilities after viewing their performance.

The self-efficacy and self-concept self-ratings are contingent on the participants' immediate performance. Outside the context of the present experiment, these ratings provide little in terms of understanding participants' sustainable attitudes about mathematics. To preserve this context, ratings were converted into difference scores that include final test accuracy. These modified dependent measures could then be used to determine the influence that math anxiety, academic attitudes, and math ability may have on these ratings. Pre-Feedback Judgment reveals how accurately participants can judge their abilities by taking the scaled difference of self-efficacy ratings and final test accuracy; a score less than 0 would indicate an underestimate of their abilities. Post-Feedback Assessment is interpreted as how harshly participants assess their performance by taking the scaled difference of self-concept ratings and final test accuracy; a score less than 0 would indicate a more punitive approach to one's abilities.

All participants underestimated their abilities, $t(129) = -17.189$, $p < .001$. Final test accuracy was underestimated on average 22.1%. Participants were also significantly punitive in judging their performance, $t(129) = -11.499$, $p < .001$. Participants gave on average self-concept ratings 20.3% less than their actual performance.

Math anxiety and math ability significantly interacted when analyzing pre-feedback judgment, $F(1,126) = 6.390$, $p < .05$. When participants have low math anxiety, judgments are equivalent across math ability groups (see Figure 22). When math anxiety is high, low math ability participants underestimate their performance significantly more than high math ability participants. The difference between low and high math anxiety among low math ability participants is only marginally significant, $F(1,126) = 2.873$, $p = .093$. This interaction is supplemented by a main effect of math ability, $F(1,126) = 4.471$, $p < .025$. Participants with high math ability were significantly more accurate in their pre-feedback judgment of their performance in modular arithmetic.

All other main effects and interaction with implicit theories of intelligence, academic goals, effort beliefs, and responses to failure for pre-feedback judgment and post-feedback assessment were non-significant, *p*s > .10 (see Table 9 for means and standard errors).

Math Equations

Similar to Experiment 1, at the end of the modular arithmetic task, participants were asked to complete a word equation by formulating the contributions that effort and ability play into math intelligence. Of the 130 participants, 38 were excluded from these analyses because their totals did not equal 100%. As predicted, those 38 participants scored significantly lower on a measure of math ability ($M = 28.2$, $SE = 0.81$) than participants with math equation sums equaling 100% ($M = 31.2$, $SE = 0.49$), $t(128) = 3.284$, $p < .001$; participants who summed incorrectly were not significantly different on measures of math anxiety or academic attitudes, *p*s > .10. Among all participants, there is a main effect of math equation weightings; participants indicated that effort significantly contributes more to math intelligence than ability, *p*s < .01.

Interactions of equation component weightings and the between-subjects factors math anxiety, incremental theory, academic goals, effort beliefs, attributions to failure and math ability were non-significant, *p*s > .10. However, despite the non-significant interactions, one-sample *t*-tests on effort weightings corrected for inflated type-I error found that the groups medium math anxious, incremental and entity theorists, learning goals, high effort beliefs, helpless-oriented, and both levels of math ability all placed significantly more emphasis on effort in contributing to math intelligence, *p*s < .025.

Gender and Task Order

Similar to the analyses in Experiment 1, gender and task order effects were repeated for Experiment 2. There were 63 males and 67 females in Experiment 2. Task order was again evenly split among the participants; 65 participants performed the task after the between-subjects measures, 65 completed the measures after the modular arithmetic task. A non-significant chi-square analysis found similar distributions of gender by task order, $p > .05$.

Measures

The main effect of gender and the gender by task order interaction were non-significant with math anxiety, *F*s < 1. However, there was a marginally significant main effect of task order, $F(1,126) = 2.948$, $p = .088$. Ratings of math anxiety were higher after learning modular arithmetic ($M = 23.0$, $SE = .79$) than ratings before the task was introduced ($M = 21.1$, $SE = .78$). Interactions and main effects of gender or task order were non-significant for implicit theories of intelligence, academic goals, effort beliefs, and attributions to failure, ps > .10.

For math ability, both main effects for gender and task order were significant; $F(1,126) = 5.930$, $p < .025$, and $F(1,126) = 9.388$, $p = .005$, respectively (see Figure 23). However, the interaction was non-significant, $F < 1$. Males performed significantly better on the WRAT than females. Participants that completed the WRAT before the modular arithmetic task scored higher than those that took the WRAT after.

Training

Gender and task order were analyzed in a 2 x 2 between-subjects ANOVA with time spent viewing the example statements as the dependent variable. The main effect of task order is marginally significant, $F(1,126) = 3.388$, $p = .068$. Participants that completed the measures first viewed the example statements for less time ($M = 91.9$ s, $SE = 4.45$ s) than participants that began with the modular arithmetic task ($M = 104$ s, $SE = 4.50$ s). Participants may have attempted to progress through the task quicker after completing thirty to forty minutes of measures. The interaction of task order and gender, the main effect of gender, and all interactions of task order or gender with math anxiety, academic attitudes, or math ability were non-significant, ps > .10. Participants were beginning the final test of Experiment 2 with the same knowledge of modular arithmetic.

Final Test

Analyses of final test performance were conducted similarly to Experiment 1. Gender and task order were added as between-subjects factors in each of a multivariate 2 x 2 x 2 within-subjects ANOVA. Within-subjects factors included true versus false statements, small versus large statements, and statements with or without a borrow operation. Dependent variables were response times and error rates. Further analyses then combined gender and task order each with another between-subjects variable.

Gender and borrow interacted significantly for both response times and error rates, $F(1,128) = 9.806$, $p < .005$, and $F(1,128) = 13.510$, $p < .001$, respectively. Beyond the significant main effects of gender in which females were slower and made more errors than males, more difficult statements with borrow operations created a greater discrepancy in performance between the genders (see Figures 24-25).

Gender and implicit theories of intelligence were also significant for both response times and error rates, $F(1,126) = 6.595$ $p < .025$, and $F(1,128) = 5.066$, $p < .05$, respectively. For response times, males and females significantly differed in response times when they were both entity theorists; responses times were statistically equivalent between genders for incremental theorists (see Figure 26). Simple effects indicated that incremental and entity theorists within the male and female groups were only marginally different, $p = .054$, and $p = .094$, respectively. The reverse happened for error rates (see Figure 27). Males and females were significantly different when they were both incremental theorists; responses times were similar between genders for entity theorists. However, male entity theorists committed significantly more errors than male incremental theorists, $F(1,126) = 4.433$, $p < .05$. There was no significant effect of theory of intelligence on error rates within females.

There was a significant interaction between task order and borrow, $F(1,128) = 6.897$, $p < .01$. Participants that completed the task first were significantly slower across all conditions, $F(1,128) = 10.047$, $p < .005$. For statements with a borrow operation, participants that performed the task first were approximately another 300 ms slower than those participants that completed the measures first (see Figure 28).

Self-efficacy and Self-concept

Pre-feedback judgment and post-feedback assessment measures described earlier were analyzed with gender and task order variables. There was a significant main effect of gender on pre-feedback judgment, $F(1,126) = 28.427$, $p < .001$. Females ($M = -22.6$, $SE = 1.31$) underestimated their performance more than males ($M = -12.5$, $SE = 1.36$). Before they viewed their accuracy, females were rating their self-efficacy on average 28.2% worse than their actual performance.

Gender and math anxiety marginally interacted in post-judgment assessment, $F(1,126) = 2.985$, $p = .087$. Simple effects demonstrated that low math anxious females were significantly more punitive in assessing their performance than low math anxious males, $F(1,126) = 4.092$, $p < .05$, (see Figure 29). However, math anxiety groups did not differ within genders and high anxiety participants were statistically equivalent across gender, *p*s > .10.

Including gender in the analysis created a main effect of implicit theories of intelligence in pre-feedback judgment, $F(1,126) = 4.627$, $p < .05$. Participants with incremental theories of intelligence ($M = -19.4$, $SE = 1.27$) were giving lower estimates of their performance than entity theorists (M = -15.4, SE = 1.35). Consistent with the social-cognitive model of motivation, participants with entity theories may be focusing more attention on performance, therefore providing them with more accurate estimates of their abilities.

Math Equations

Main effects and interaction involving gender and task order with any of math anxiety, academic attitudes, or math ability measures were non-significant, ps > .10. One-sample t-tests analyses determined that only females that completed measures first placed significantly more emphasis on effort (M = 58.2, SE = 3.69), $t(18) = 2.210$, $p < .05$. Males, regardless of task order, were marginally significant in their emphasis in effort, ps < .10. Females who completed the task first placed similar emphasis on effort and ability, $t(24) = 1.134$, $p > .10$.

Discussion

Contrasted with the self-study session in Experiment 1, instructions in Experiment 2 were effective in teaching participants how to solve modular arithmetic. Only six of the 130 participants had scores on the final test within the range of chance performance; that is, fewer than 48 statements answered correctly (the performance for these six participants is attributed to a propensity to respond false considerably more than their peers). The effective training led to results regarding problem difficulty that were consistent with past research (Ashcraft & Faust, 1994; Ashcraft & Krause, 2007; Zbrodoff & Logan, 2005). Increasing problem difficulty by either increasing the size of the operands or by necessitating a borrow operation significantly impacted performance by lengthening response times and increasing errors, with the most difficult problems causing disruptions more than the sum of their parts.

However, the main hypotheses of Experiment 2 were not supported. Specifically, the results did not provide evidence that participants with entity theories of intelligence or related attitudes within the social-cognitive model of motivation had fewer available cognitive resources. Believing intelligence to be a fixed trait, pursuing or avoiding displays of performance, viewing effort as an indication of low ability, and retreating from failure did not consume enough mental resources to cause compounding decreases in performance when statements were more difficult to solve. Furthermore, inconsistent with past research, participants with high math anxiety performed similarly to participants with low math anxiety. Past research has suggested that math anxiety consumes cognitive resources, thus impairing learning and disrupting performance on problems with higher cognitive load (Ashcraft & Kirk, 2001; Beilock & Carr, 2005; Beilock, Kulp, Holt, & Carr, 2004). It was the goal of this thesis to replicate the math anxiety effect and additionally demonstrate the same effect with entity theories of intelligence. Explanations for this null effect and its impact on the theories will be discussed in more detail in the General Discussion.

Consistent with the results of Experiment 1, math ability was a prominent predictor in determining performance for Experiment 2. Participants that are better at math are more efficient in terms of response times and error rates than low math ability participants. The advantage in the academic setting is profound because participants entering a class containing new math concepts can apply new techniques with greater proficiency minutes after instruction. Additionally, participants with high math ability were more adept at assessing their performance in a self-efficacy rating before viewing their final test feedback, especially if they were also high math anxious. Consistent with the predicted relationship among math anxiety and the social-cognitive model of motivation, participants with high anxiety and high math ability focus more on their performance, therefore providing better estimates of their abilities. Participants with both high math anxiety and low math ability disengage themselves from the domain and considerably underestimate their performance.

The social-cognitive model of motivation explains the task performance of males. Males with entity theories resembled the speed-accuracy trade-off found among high math anxious participants in the literature: statements were solved more quickly and, as a result, there were more errors (Faust, Ashcraft, & Fleck, 1996). Thoughts and attitudes focused on intelligence as a fixed trait may be consuming cognitive resources that should instead be delegated towards completing the math task. Results from the final test suggest that females had fewer cognitive resources to effectively solve more difficult statements. Yet, these disruptions were not caused by math anxiety or attitudes related to the social-cognitive model of motivation. Females with entity theories performed as well as females with incremental theories of intelligence. Another affective component not measured in the experiment was consuming limited cognitive resources in females but not males.

Results suggest that the task may have created another stereotype threat like effect in females, whereas males were performing as predicted by the literature. In addition to poor task performance, females scored considerably worse on the measure of math ability, were less confident in their task performance before they viewed their feedback, and judged their performance more harshly. However, contrasted with Experiment 1, the modular arithmetic task here did not provide a scenario of failure that may have led to an effect analogous to a stereotype threat. Learning a new math task in itself, regardless of failure, may be enough to elicit negative attitudes towards math, which disrupt learning and performance. More research is necessary to isolate the mechanisms that may be creating these disruptions and if those mechanisms are rooted in the social-cognitive model of motivation.

CHAPTER 4

GENERAL DISCUSSION

This study examined the relationship between the social-cognitive model of motivation and math anxiety by exposing participants to a novel math task. The goal of Experiment 1 was to show that implicit theories of intelligence and related attitudes along the spectrum could predict and explain participant's behavior during a mathematics task in a laboratory setting. The goal of Experiment 2 was to demonstrate that implicit theories of intelligence and the related academic attitudes explain local, online cognitive deficits during a mathematics test. It was also hypothesized that the cognitive effects of those attitudes would relate to the well-established cognitive effects of math anxiety and stereotype threat. In predicting behavior, explaining cognitive deficits, and relating to recognized math cognition theories, the social-cognitive model of motivation could begin to establish itself as the framework from which attitudes about math lead to mathematical understanding.

However, the results from this thesis only found marginal support for the model's theorized role. Attitudes from the model did not influence participants' behavior or performance when learning a new math task. Math anxiety was also insufficient in explaining learning or performance. Differences between males and females proved essential in understanding how the social-cognitive model of motivation explains participants' behavior in the novel tasks. Behavior of males characterized the predicted effects; those with incremental theories were more engaged in the task. In contrast, females appeared to undergo an effect similar to a stereotype threat. Finally, math ability was the most significant factor in predicting outcomes in math tasks. Participants with high math ability were able to learn new math tasks more effectively and perform math algorithms with greater efficiency.

As discussed, results did not always follow the predicted outcomes. However, patterns in the observations suggest possible explanations for the data. For example, an important part of Experiment 1 was activating the relevant attitudes of the social-cognitive model of motivation. Much of the research examining the model relies on instances of failure or struggle to highlight incremental or entity related behaviors (Blackwell et al., 2007; Hong et al., 1999; Mueller & Dweck, 1998). It is possible that chance performance on the initial test was not satisfactory in triggering attitudes related to implicit theories of intelligence. Although chance performance is technically failing, incrementally oriented participants may have felt correctly answering five out of ten statements on a math task they have never seen before did not require an urgent need for rigorous study; or more simply, chance performance was satisfactory performance for an inconsequential psychology experiment.

Results suggest that failing the initial test was sufficient in triggering the predicted effort and withdrawal behaviors of males. However, for females, failing the initial test appears to have instead created an effect similar to a stereotype threat. Replicating the results of standard stereotype threat scenarios (Beilock, Rydell, & McConnell, 2007; Good, Aronson, & Harder, 2008; Johns, Schmader, & Martens, 2005), females performed poorly on the math ability assessment only if they completed it after completing the difficult math task. Furthermore, if failing the initial test elicited perceptions related to stereotype threat, then females may have had fewer cognitive resources to teach themselves the correct solution algorithm. Although math ability predicted if a participant determined the correct method, high math ability females were just as unlikely to determine the algorithm as low math ability females. However, high math ability males were likely to infer the solution; 14 of the 22 participants that determined the method were males with high math ability. Females with entity theories of intelligence and high math ability studied the most examples for the longest time; however, they could not integrate their superior math knowledge in to learning the new task because their cognitive resources were consumed by the stereotype threat.

Interestingly, Experiment 2 did not expose participants to a scenario of failure and females still scored lower on the assessment of math ability, performed poorer on the modular arithmetic task, and were considerably less confident in their abilities. It is possible that convenient sampling provided a group of females who were by chance less skilled in mathematics. However, examining the data further suggests that the gender difference in math ability is actually from males performing better than average (Steiner & Ashcraft, 2012). Additionally, female performance during the final test was influenced by problem difficulty more than males, suggesting disruptive cognitive resources unrelated to baseline math ability. Learning a new math task may activate the threat by creating the possibility of failure, as demonstrated in females' pre-feedback judgment of their performance.

A crucial difference with the experiments in this thesis and previous studies within the math cognition literature is that the final tests did not contain trial-to-trial feedback. Without this feedback, negative attitudes about math may not have been provoked enough to disrupt cognitive processing. Accordingly, attitudes regarding entity theories of intelligence, performance goals, negative effort beliefs, and helpless responses to failure may have failed to surface and disrupt cognitive processes susceptible to increased problem difficulty. However, for the purposes of Experiments 1 and 2, eliminating feedback was important to prevent the confound of learning during the final test. Although the experiments were different enough to prevent direct comparisons in performance, results from both suggest that participants with varying attitudes within the social-cognitive model are comparable to each other in terms of teaching themselves a novel math task and learning a novel math task from simple instruction. Furthermore, different sets of attitudes across the spectrum do not appear to systematically interfere with cognitive resources engaged in the math task.

Just as the concern exists with any research using self-report surveys, this thesis is limited by the reliability and validity of the measures used. The scales measuring the social-cognitive model of motivation may not be appropriate in measuring attitudes that would influence performance in the current study within a collegiate setting. The academic attitudes in this thesis indicated that college students are more likely to maintain incremental theories of intelligence, have positive beliefs about effort, and be mastery-oriented in response to failure. Among participants that favored performance goals, learning was still an essential academic goal. Similarly, all participants emphasized effort over ability as the strongest contributor to math intelligence. The selection processes of a university decrease the likelihood that students would favor entity theories and the attitudes that follow; in the current study, less than 6% of students could be classified onto the entity end of the theory of intelligence continuum. Consequently, students are far enough along the incremental end of the continuum that changes in either direction may not have led to quantitative differences in behavior when learning a novel mathematics task or measurable impacts on performance. Future studies should attempt to recruit participants with more variability along the social-cognitive model of motivation spectrum or by sampling outside of the college population.

Yet, regardless of the limitations of the social-cognitive model of motivation in this thesis, the scales were internally consistent. Stronger incremental scores related to more positive beliefs about effort, adoption of learning goals, and mastery responses to failure. Therefore, non-significant findings within this study are less likely a result of a failure to measure the social-cognitive model of motivation in college students and more likely due to a lack in variability of those attitudes across the available sample.

One of the goals of this thesis was to establish a theoretical connection between math anxiety and the social-cognitive model of motivation. However, without manipulating either construct experimentally the results can only provide conjecture about their relationship. Yet, as hypothesized, participants with high levels of anxiety were more likely to favor displaying high levels of performance instead of learning, viewed effort as an indication of low ability and low intelligence, and attributed academic failure to low intelligence. Furthermore, participants were more likely to weigh effort over ability as the significant contributor to math intelligence only if they were low math anxious. The social-cognitive model of motivation may provide the definitive framework for understanding why and when math anxiety disrupts learning and performance in mathematics.

Further studies should continue to explore the possible relationships among the social-cognitive model of motivation and attitudes towards mathematics, and furthermore, the cognitive disruptions that may occur during learning and assessments of mathematics. Experimentally manipulating participants' implicit theories of intelligence may reveal the hypothesized behavioral and cognitive effects. Many studies have primed entity or incremental theories to reveal significant behavioral outcomes (Burns & Isbell, 2007; Dweck, 1999; Murphy & Dweck, 2010). A similar manipulation in this context may elicit different studying habits in learning modular arithmetic and also cognitive deficits replicating the math anxiety research. Future experiments may also elicit stronger attitudes and anxieties by providing more immediate or salient types of performance feedback. For example, trial-to-trial feedback has been found to elicit stronger anxiety responses (Eysenck & Calvo, 1982, Olvet & Hajcak, 2009). These responses may also reveal significant cognitive differences in participants with entity or incremental theories of intelligence.

More importantly, the significant gender effects found in this thesis should be explored in greater detail. The results support the notion that females are at greater risk of experiencing the learning and performance deficits due to, not just negative attitudes about math, but also entity related attitudes of the social-cognitive model of motivation. However, in this thesis, the stereotype was not explicitly aroused. Instead, the results suggest that exposing females to failure in a math task, instructing them to learn on their own the correct solution algorithm, or simply teaching them a novel math task was enough to duplicate the typical performance deficits of a stereotype threat condition. This may suggest that the cognitive mechanisms of stereotype threat may be closely related to attitudes responsible for entity spectrum of the social-cognitive model of motivation. A follow up study using previously established stereotype threat techniques in the same setting and task conditions combined with manipulating theories of intelligence may specify the disrupting cognitive processes when learning and performing math.

In summary, this thesis did not show specific evidence establishing the social-cognitive model of motivation as the definitive framework that explains the constellation of positive and negative attitudes affecting math performance. However, results demonstrating clear relationships among attitudes of the model, math anxiety, and gender suggest a productive line of research that could eventually determine how the social-cognitive model of motivation creates global and local cognitive deficits to mathematics understanding.

APPENDIX A: TABLES

Table 1

Descriptive Statistics for Between Subjects Factors

			Group Sizes	
	M (SD)	*Median*	Experiment 1	Experiment 2
Math Anxiety	22.5 (6.29)	22.0		
Low			28	47
Medium			29	45
High			35	38
Implicit Theory	4.59 (0.91)	4.63		
Entity			40	61
Incremental			52	69
Academic Goals				
Performance	4.59 (0.96)	4.67	49	75
Learning	4.42 (0.91)	4.33	43	55
Effort Beliefs	4.72 (0.59)	4.78		
Negative			44	58
Positive			48	72
Attributions to Failure	4.96 (0.68)	5.00		
Helpless			37	63
Mastery			55	67
Math Ability	30.24 (4.89)	30.0		
Low			51	65
High			41	65

Table 2

Correlations of Math Anxiety, Academic Attitudes, and Math Ability

Measure	*1*	*2*	*3*	*4*	*5*	*6*
1. Math Anxiety	-					
2. Implicit Theory	-.048	-				
Academic Goals						
3. Performance	.175**	.131	-			
4. Learning	-.043	.211**	-.099	-		
5. Effort Beliefs	-.158*	.369***	.015	.407***	-	
6. Attribution to Failure	-.166*	.332***	-.034	.318***	.505***	-
7. Math Ability	-.173**	.010	-.143*	.081	-.020	-.001

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table 3

Initial Test Response Times and Error Rates

	Response Times (ms)		Error Rates	
	M	*SE*	*M*	*SE*
Math Anxiety				
Low	3945	301	.429	.037
Medium	3975	324	.428	.034
High	4661	243	.440	.030
Implicit Theory				
Entity	4250	237	.422	.027
Incremental	4209	236	.440	.027
Academic Goals				
Performance	3866	198	.402	.028
Learning	4639	267	.467	.025
Effort Beliefs				
Negative	4329	249	.445	.027
Positive	1576	228	.421	.027
Attributions to Failure				
Helpless	4417	258	.476	.029
Mastery	4099	220	.404	.025
Math Ability				
Low	4400	221	.449	.026
High	4011	255	.412	.029

Table 4

Participant Behavior During Study Session

	Total Statements Viewed		Total Study Time (s)	
	M	*SE*	*M*	*SE*
Math Anxiety				
Low	18.0	2.00	116	16.9
Medium	17.1	1.81	96.5	14.4
High	16.2	1.56	94.1	12.7
Implicit Theory				
Entity	16.8	1.69	103	14.1
Incremental	17.2	1.26	100	10.2
Academic Goals				
Performance	16.8	1.43	92.6	10.5
Learning	17.3	1.46	112	13.3
Effort Beliefs				
Negative	17.2	1.48	114	13.6
Positive	16.9	1.40	90.7	9.99
Attributions to Failure				
Helpless	17.0	1.52	109	14.5
Mastery	17.1	1.37	96.7	10.1
Math Ability				
Low	14.6	1.36	84.4	9.82
High	20.1	1.40	123	13.7

Table 5

Difference Between Actual and Recalled Initial Test Performance

	Difference Score	
	M	*SE*
Math Anxiety		
Low	-0.30	0.306
Medium	-0.48	0.308
High	0.06	0.040
Implicit Theory		
Entity	-0.15	0.216
Incremental	-0.27	0.174
Academic Goals		
Performance	-0.16	0.168
Learning	-0.29	0.219
Effort Beliefs		
Negative	-0.20	0.199
Positive	-0.23	0.186
Attributions to Failure		
Helpless	-0.19	0.139
Mastery	-0.24	0.208
Math Ability		
Low	-0.26	0.173
High	-0.17	0.215

Table 6

Experiment 1: Math Equation Percentages of Effort and Ability

	Effort	Ability	
	M	*M*	*SE*
Math Anxiety			
Low	66.1	33.9	3.63
Medium	55.2	44.8	3.82
High	51.4	48.6	3.17
Implicit Theory of Intelligence			
Entity	60.5	39.5	3.23
Incremental	53.9	46.1	2.80
Academic Goals			
Performance	55.8	44.2	2.64
Learning	58.7	41.3	3.50
Effort Beliefs			
Negative	54.5	45.5	3.13
Positive	59.5	40.5	2.95
Attributions to Failure			
Helpless	52.2	47.8	3.69
Mastery	60.0	40.0	2.58
Math Ability			
Low	54.7	45.3	3.20
High	59.8	40.2	2.80

Table 7

Participant Behavior During Study Session by Gender

	Total Statements Viewed		Total Study Time (s)	
	Males	Females	Males	Females
Math Anxiety				
Low	17.6 (1.82)	17.6 (2.58)	109 (15.0)	95.0 (21.3)
High	14.7 (2.21)	17.8 (1.81)	97.1 (18.2)	100 (15.0)
Implicit Theory				
Entity	13.8 (2.04)	19.8 (2.23)	88.3 (16.9)	116 (18.5)
Incremental	18.6 (1.86)	16.3 (1.87)	118 (15.3)	86.6 (15.5)
Academic Goals				
Performance	17.5 (2.16)	16.8 (1.83)	97.9 (17.8)	92.9 (15.0)
Learning	15.6 (1.83)	19.4 (2.49)	109 (15.1)	109 (20.5)
Effort Beliefs				
Negative	17.3 (2.08)	16.8 (2.06)	118 (17.0)	107 (16.9)
Positive	15.6 (1.90)	18.6 (2.08)	93.2 (15.5)	90.0 (17.0)
Attributions to Failure				
Helpless	15.4 (2.43)	18.4 (2.13)	94.2 (19.5)	123 (17.2)
Mastery	16.9 (1.72)	17.1 (2.02)	109 (13.8)	77.1 (16.3)

Note: All means are adjusted using math ability as a covariate at the value WRAT Total = 30.11.

Table 8

Participant Behavior During Study Session by Task Order

	Total Statements Viewed		Total Study Time (s)	
	Task First	Measures First	Task First	Measures First
Math Anxiety				
Low	16.8 (1.96)	18.8 (2.28)	106 (16.2)	103 (18.8)
High	18.3 (2.07)	15.1 (1.86)	111 (17.1)	89.6 (15.3)
Implicit Theory				
Entity	16.0 (2.28)	17.0 (2.08)	102 (18.7)	99.7 (17.1)
Incremental	18.5 (1.83)	16.2 (1.97)	112 (15.0)	90.6 (16.2)
Academic Goals				
Performance	17.7 (1.99)	16.6 (1.94)	101 (16.2)	89.4 (15.8)
Learning	17.3 (2.07)	16.6 (2.15)	116 (16.9)	102 (17.5)
Effort Beliefs				
Negative	16.4 (2.06)	17.8 (2.06)	116 (16.8)	108 (16.8)
Positive	18.6 (1.98)	15.4 (1.97)	101 (16.2)	82.6 (16.1)
Attributions to Failure				
Helpless	17.0 (2.07)	17.4 (2.5)	111 (16.9)	109 (20.4)
Mastery	18.0 (1.98)	16.1 (1.75)	106 (16.1)	88.2 (14.2)

Note: All means are adjusted using math ability as a covariate at the value WRAT Total = 30.11.

Table 9

Pre-Feedback Judgments and Post-Feedback Assessments

	Pre-Feedback Judgment	Post-Feedback Assessment
Math Anxiety		
Low	-16.9 (1.29)	-16.2 (1.75)
High	-18.6 (1.67)	-16.4 (2.33)
Implicit Theory of Intelligence		
Entity	-15.9 (1.46)	-15.3 (2.03)
Incremental	-19.1 (1.43)	-17.1 (1.98)
Academic Goals		
Performance	-17.3 (1.41)	-15.4 (2.10
Learning	-18.1 (1.50)	-17.4 (1.74)
Effort Beliefs		
Negative	-17.4 (1.50)	-16.4 (2.10)
Positive	-17.8 (1.41)	-16.1 (1.92)
Attributions to Failure		
Helpless	-18.2 (1.51)	-15.8 (2.07)
Mastery	-17.1 (1.41)	-16.7 (1.95)
Math Ability		
Low	-20.1 (1.46)	-16.7 (2.14)
High	-15.3 (1.40)	-15.9 (1.86)

APPENDIX B: FIGURES

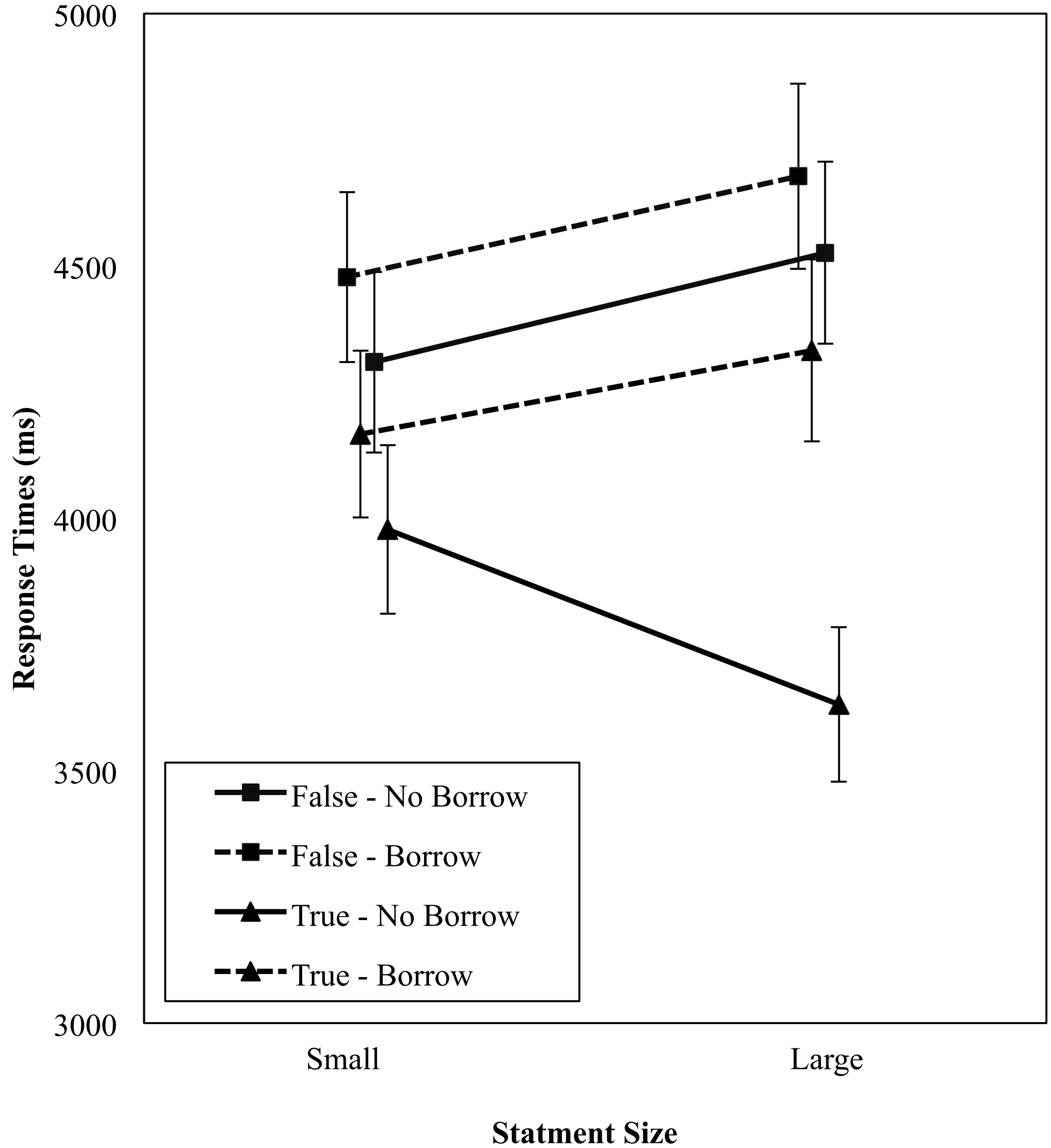

Figure 1: Response times during the final test in Experiment 1 for all three within-subjects variables true/false, statement size, and borrow. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

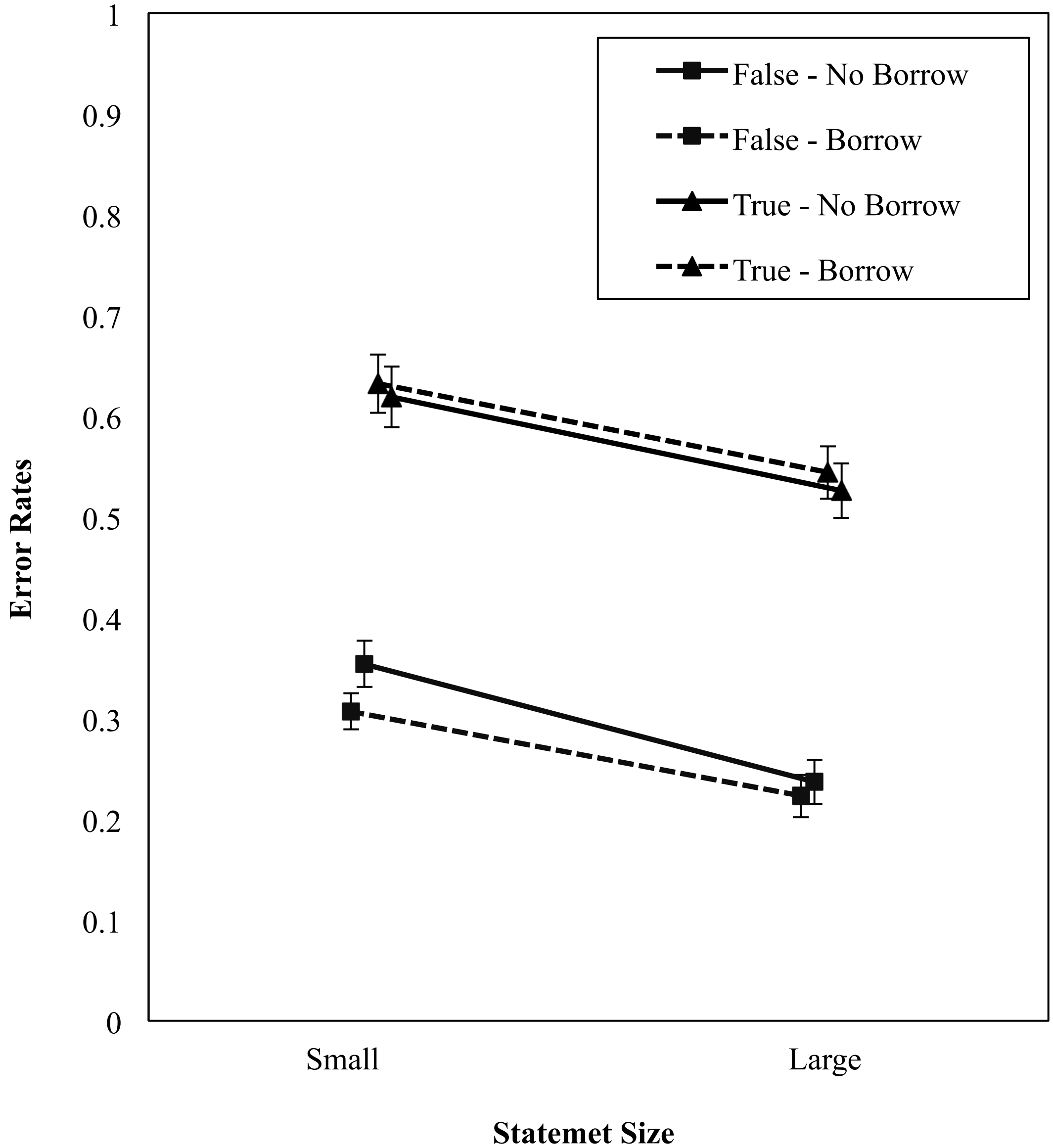

Figure 2: Error rates during the final test in Experiment 1 for all within-subjects variables true/false, statement size, and borrow. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

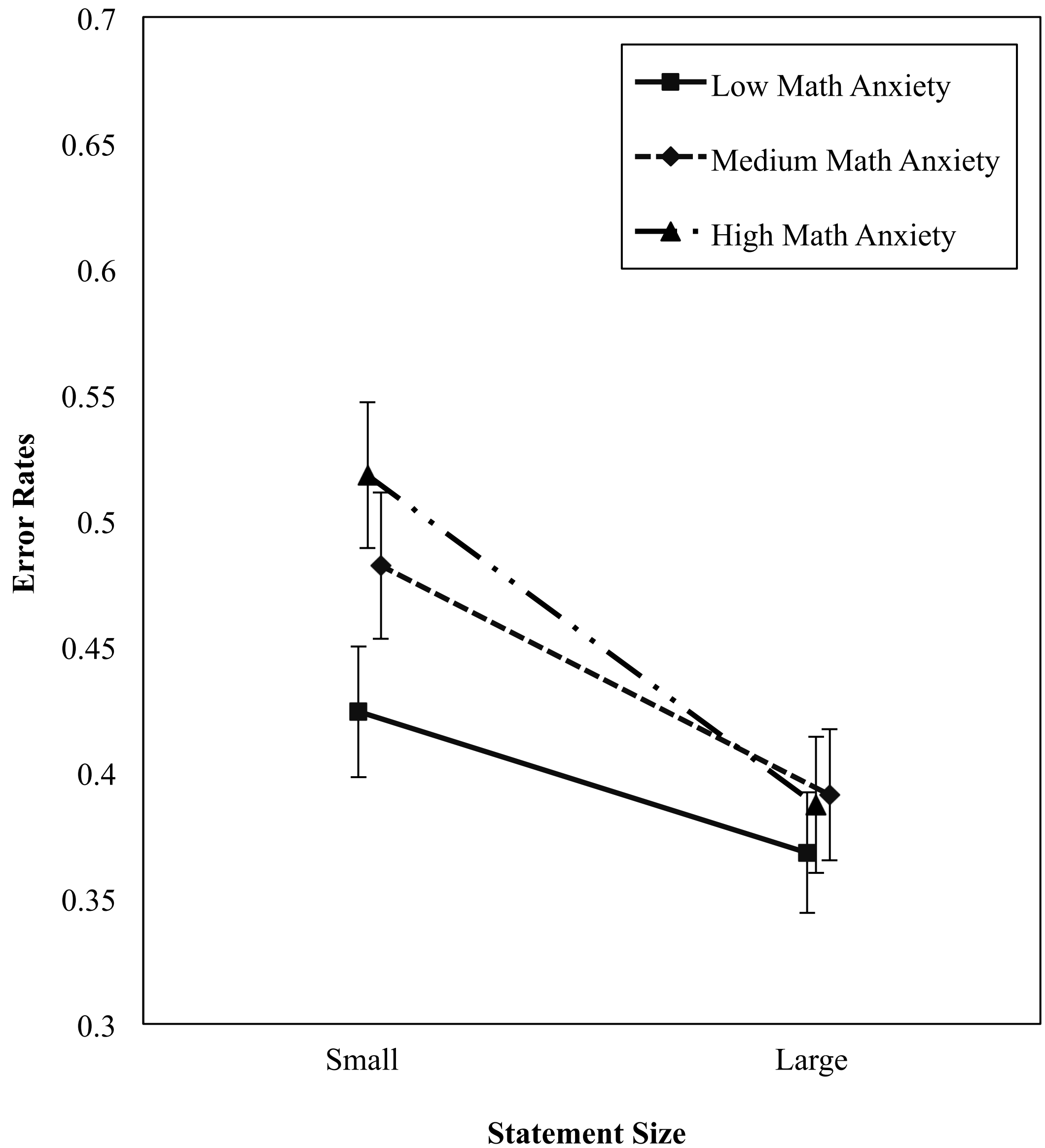

Figure 3: Error rates during the final test in Experiment 1 of math anxiety by statement size. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

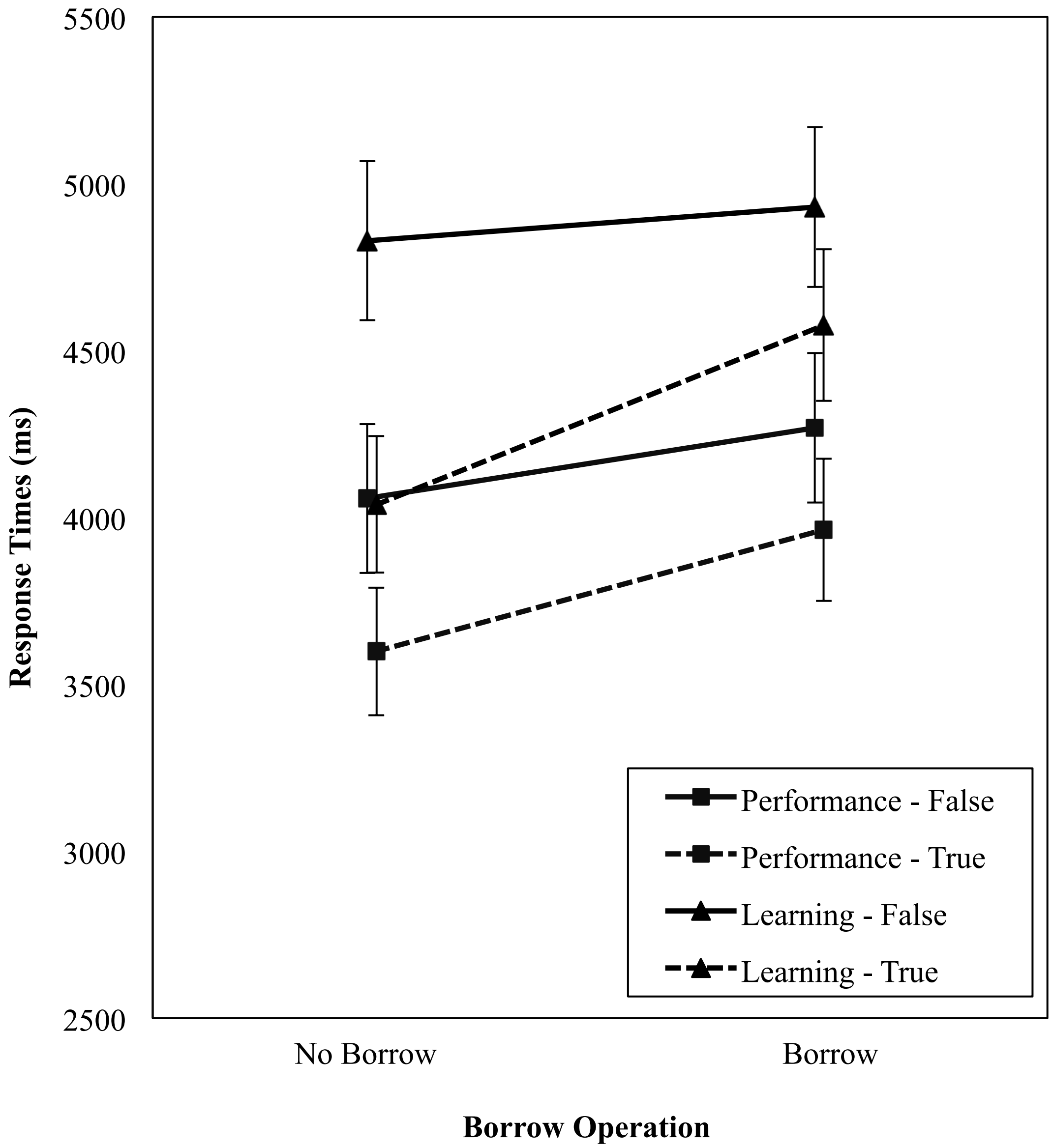

Figure 4: Response times during the final test in Experiment 1 of academic goals, true/false, and borrow. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

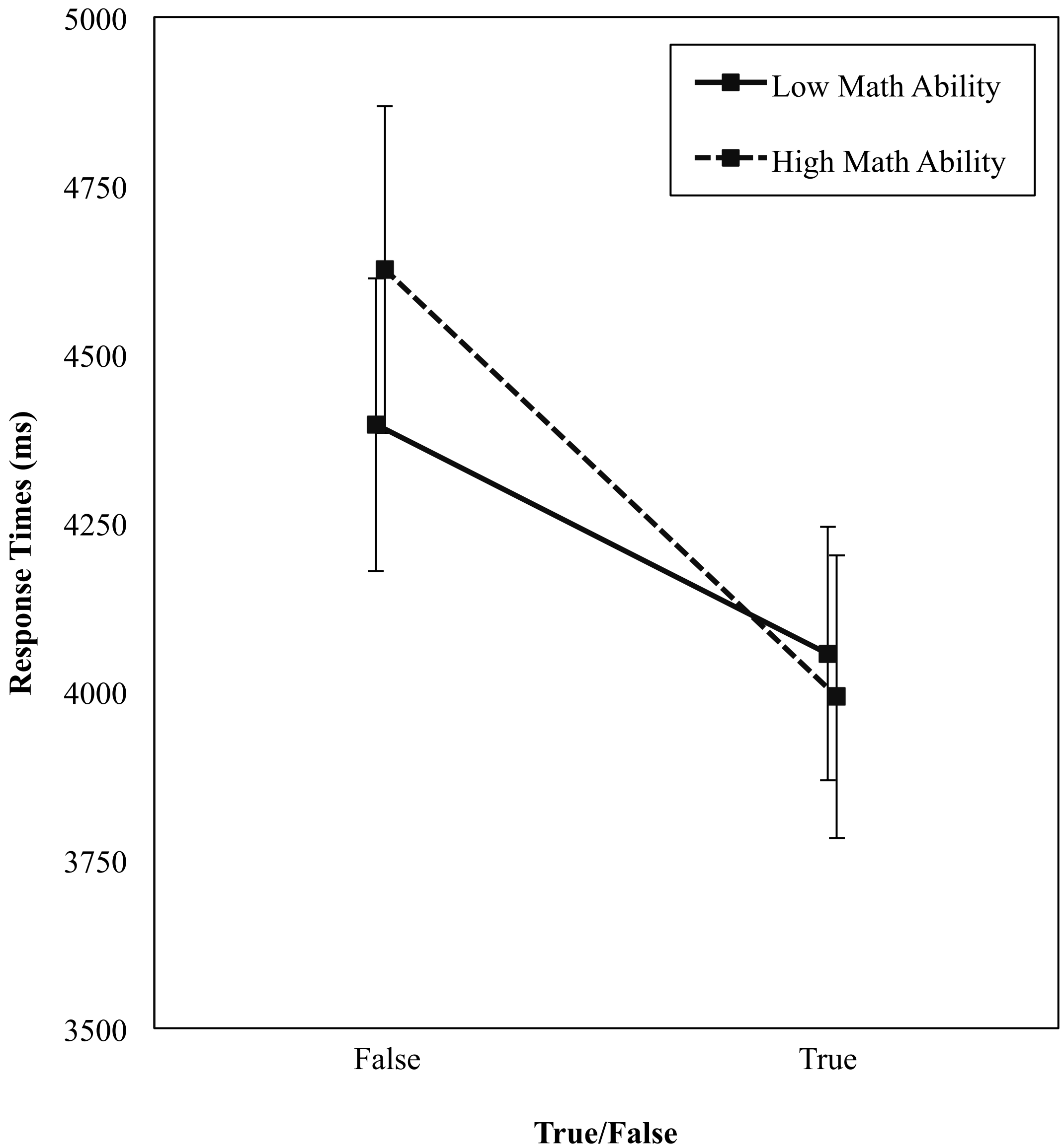

Figure 5: Response times during the final test in Experiment 1 of math ability and true/false. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

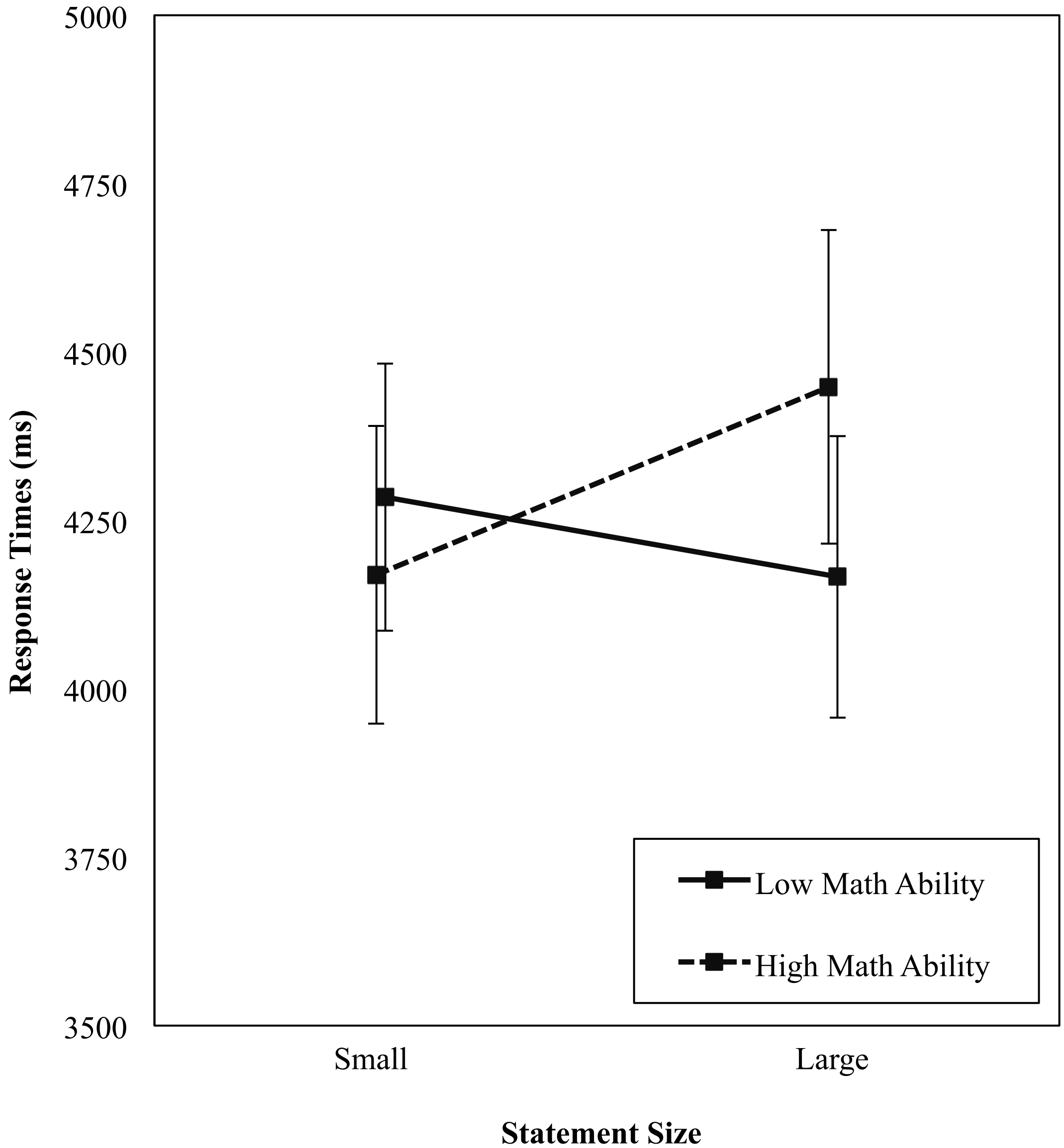

Figure 6: Response times during the final test in Experiment 1 of math ability and statement size. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

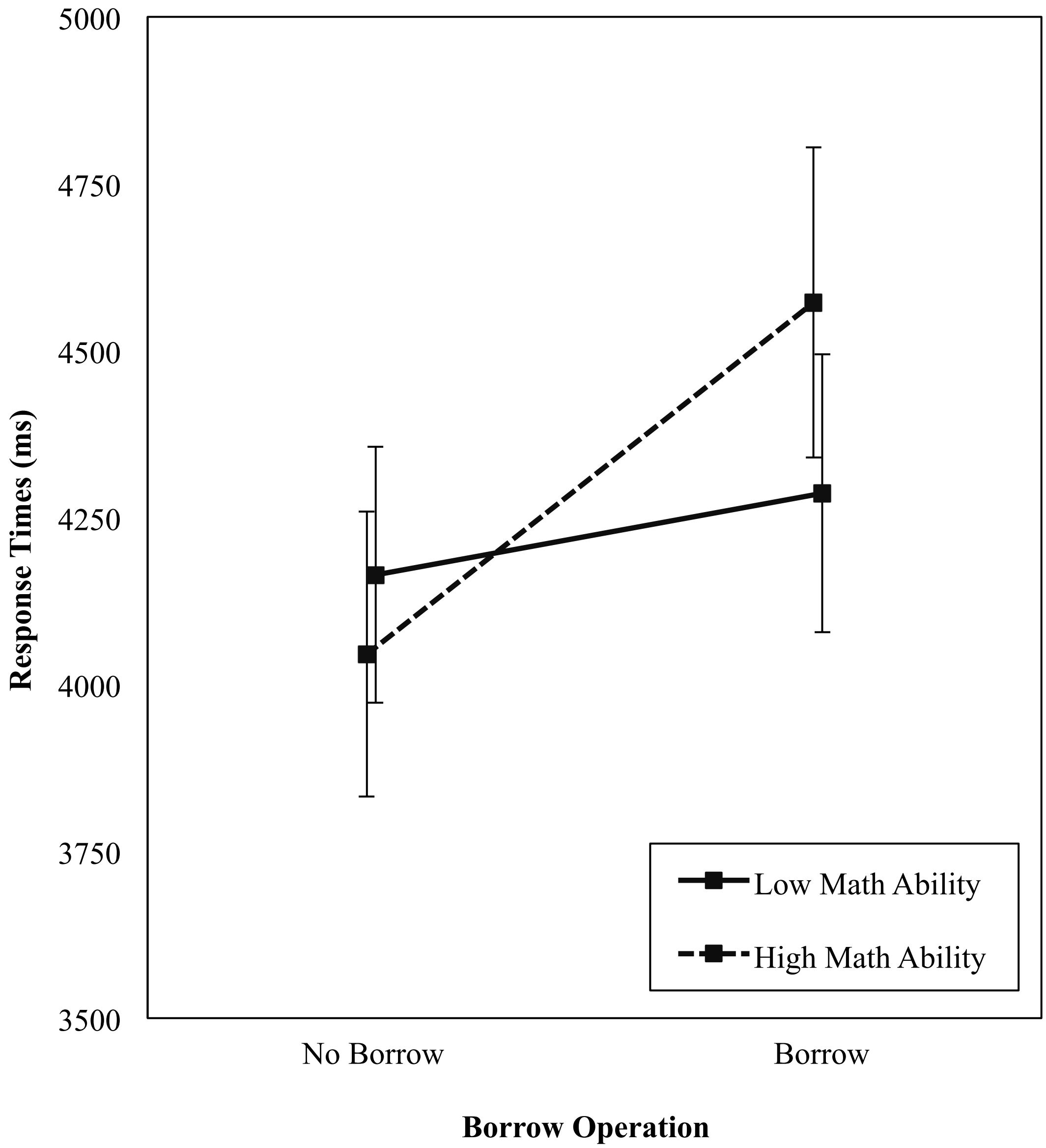

Figure 7: Response times during the final test in Experiment 1 of math ability and borrow. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

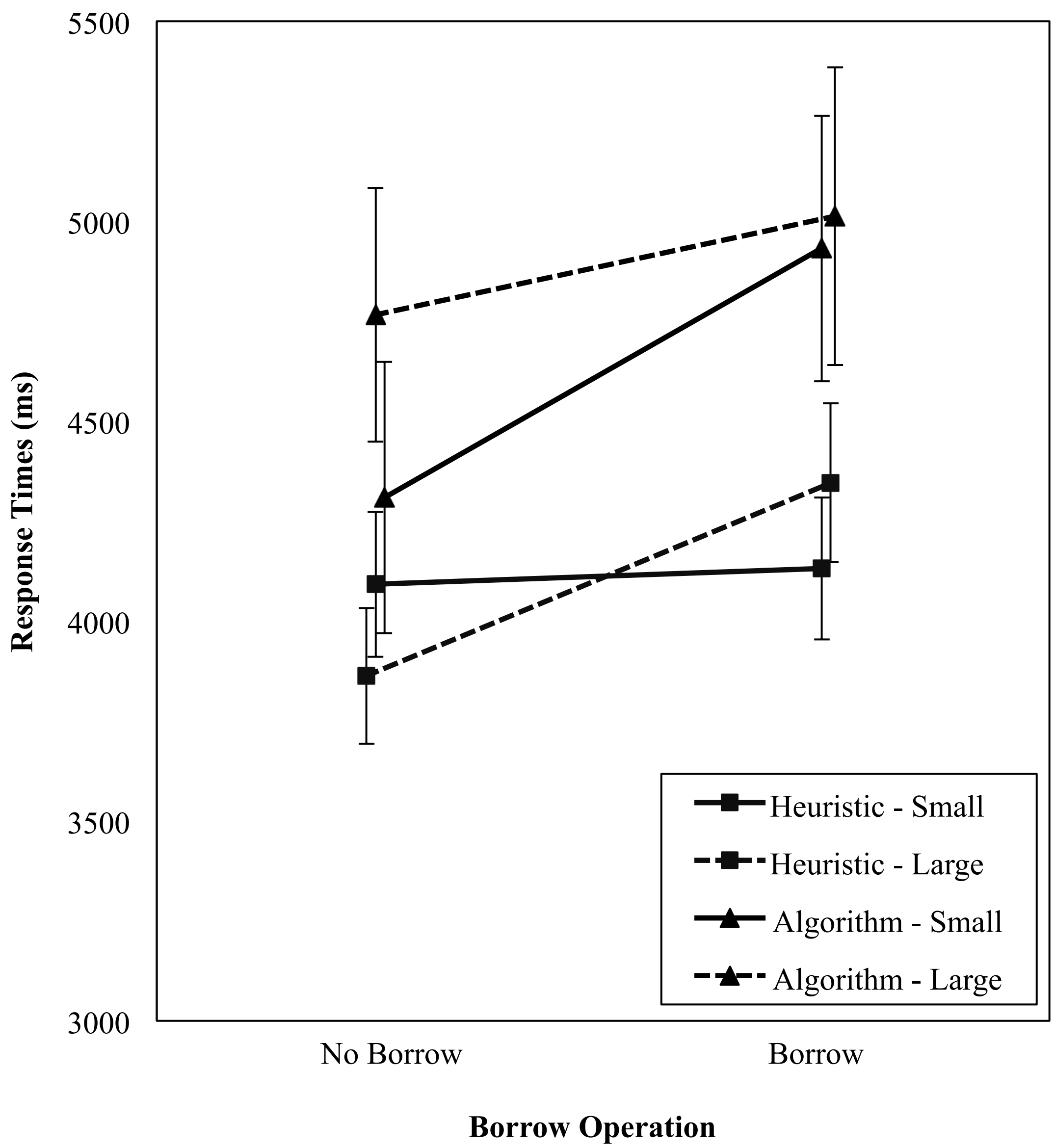

Figure 8: Response times during the final test in Experiment 1 of participants using algorithms or heuristics, with the variables statement size and borrow. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

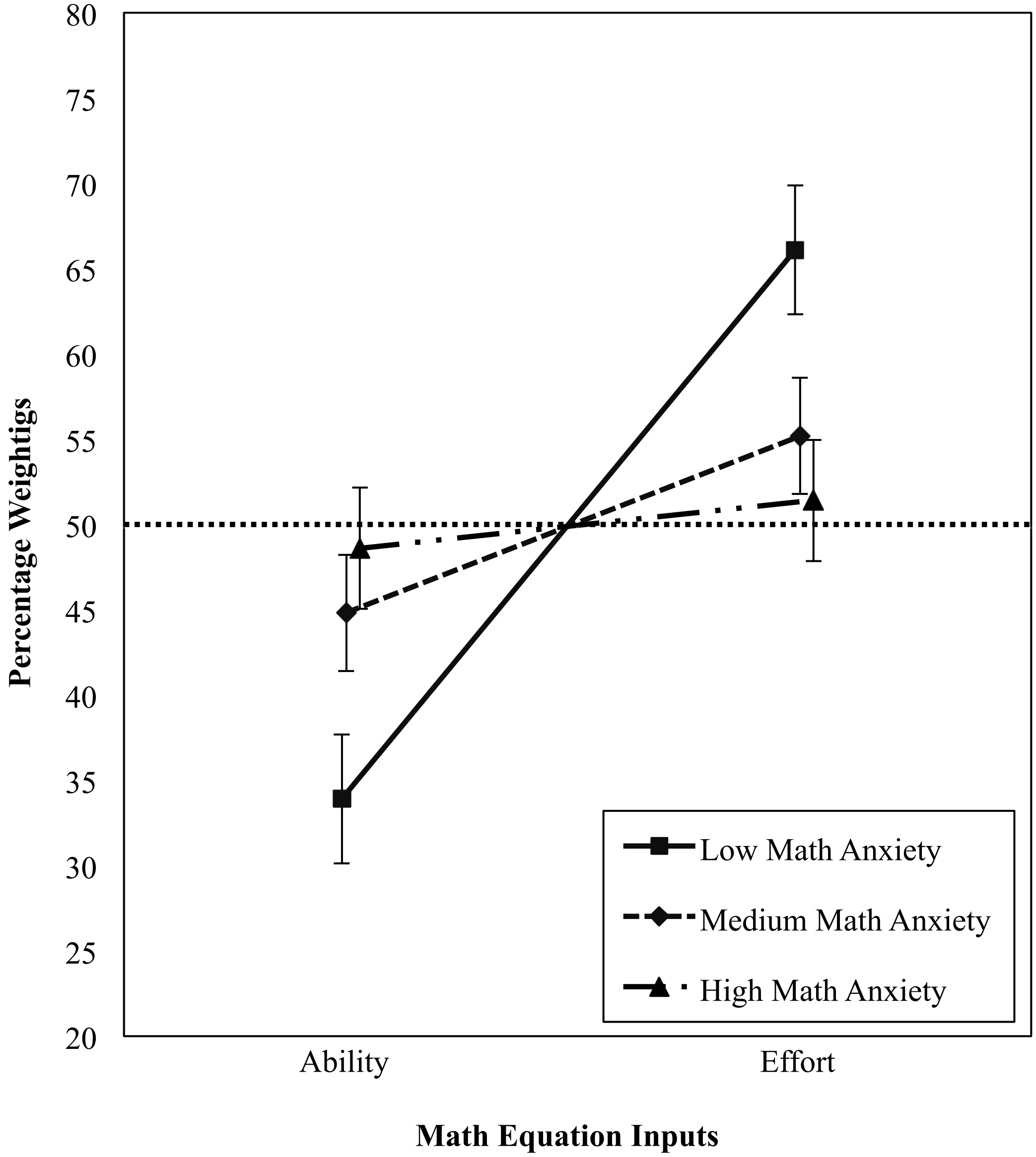

Figure 9: Weightings of ability and effort in the equation "Math intelligence = _____% effort + _____% ability" by math anxiety Group in Experiment 1. Dashed line at 50 represents equal weightings of ability and effort. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

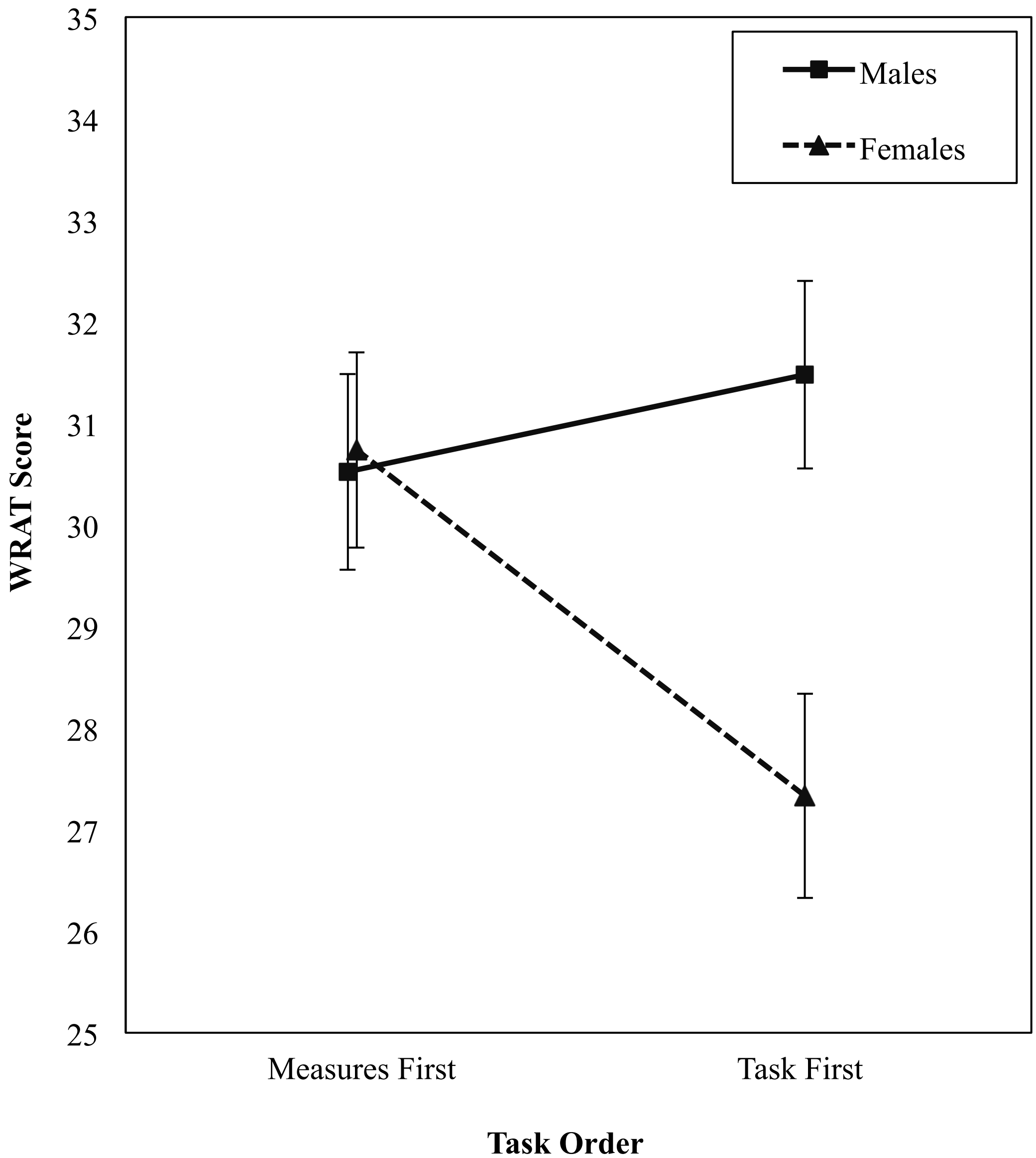

Figure 10: Measure of math ability in Experiment 1 of males and females taken either before or after the modular arithmetic task. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

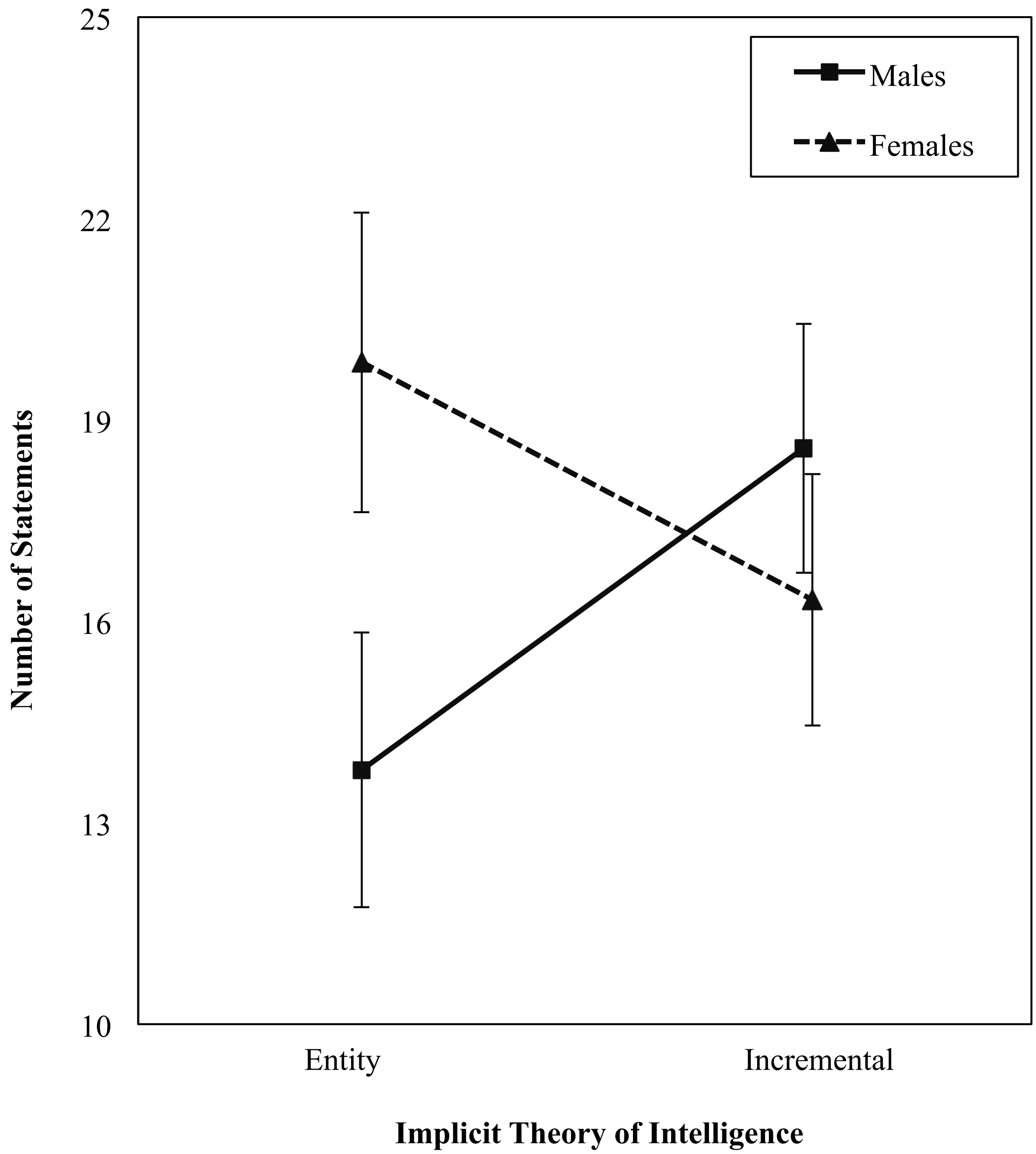

Figure 11: Number of example statements studied in Experiment 1 of males and females by entity and incremental theories of intelligence. Means are adjusted using total score on the WRAT as a covariate. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

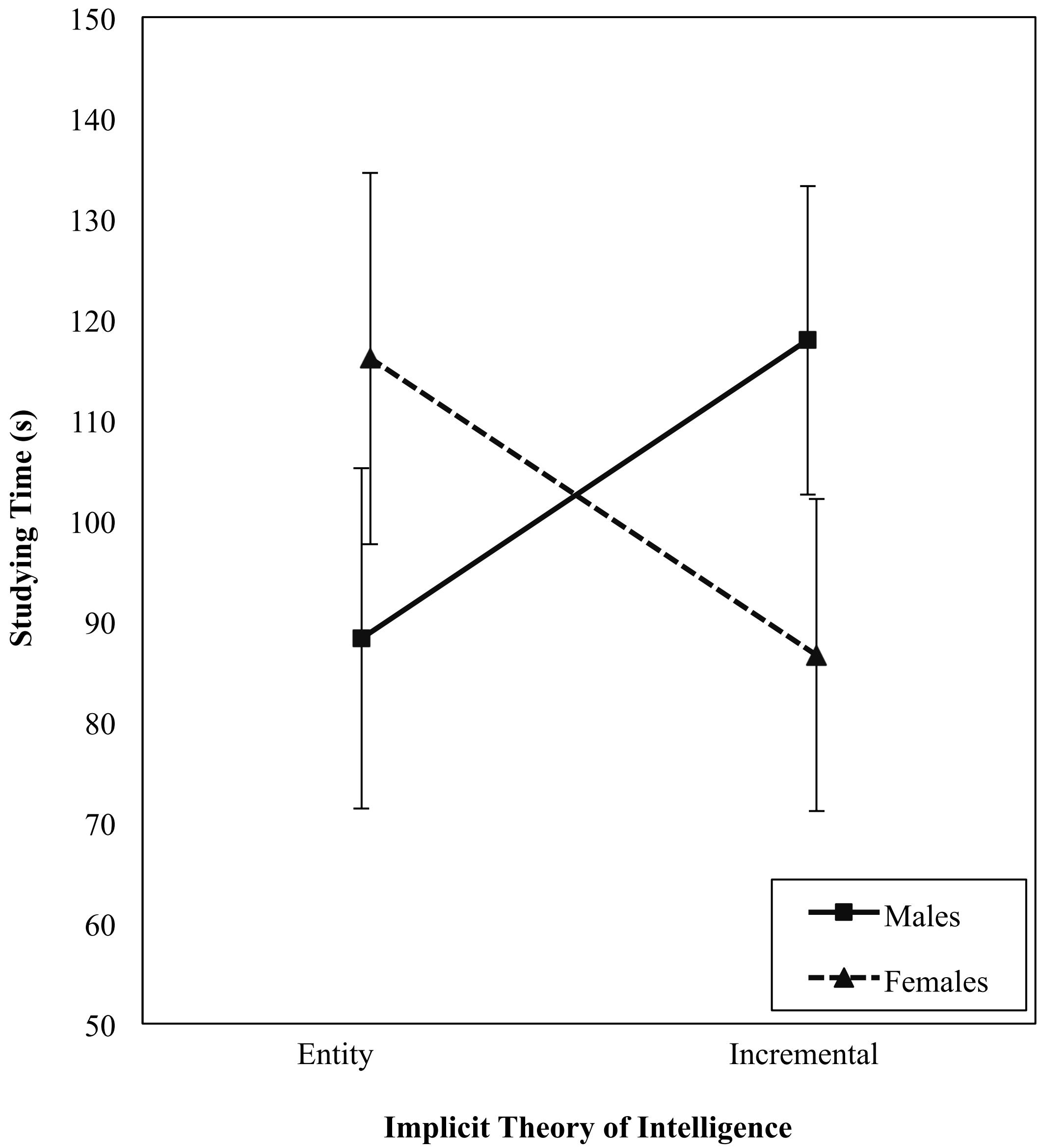

Figure 12: Seconds spent studying in Experiment 1 of males and females by entity and incremental theories of intelligence. Means are adjusted using total score on the WRAT as a covariate. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

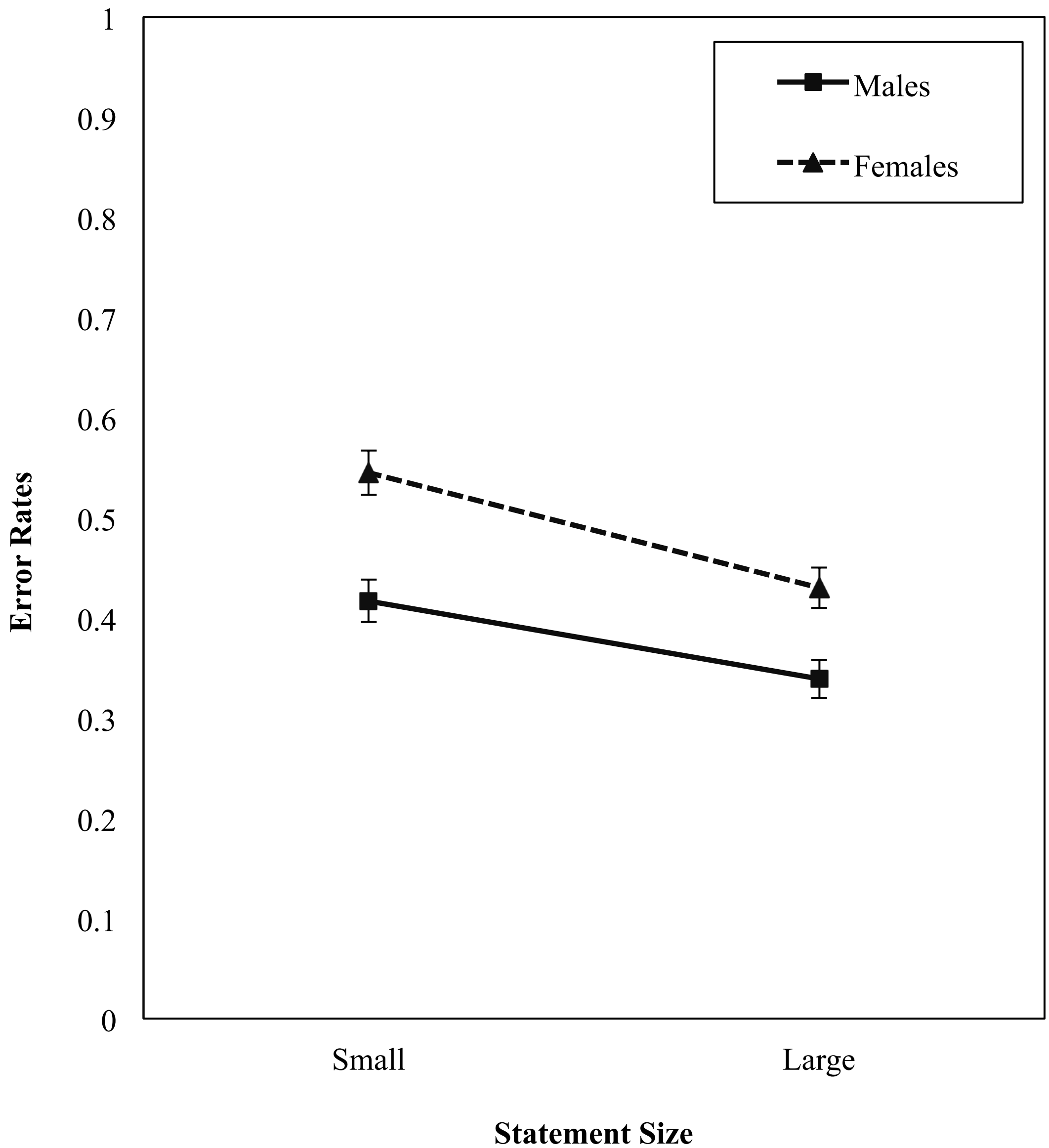

Figure 13: Error rates during the final test in Experiment 1 for all three within-subjects variables true/false, statement size, and borrow. Error bars represent standard errors.

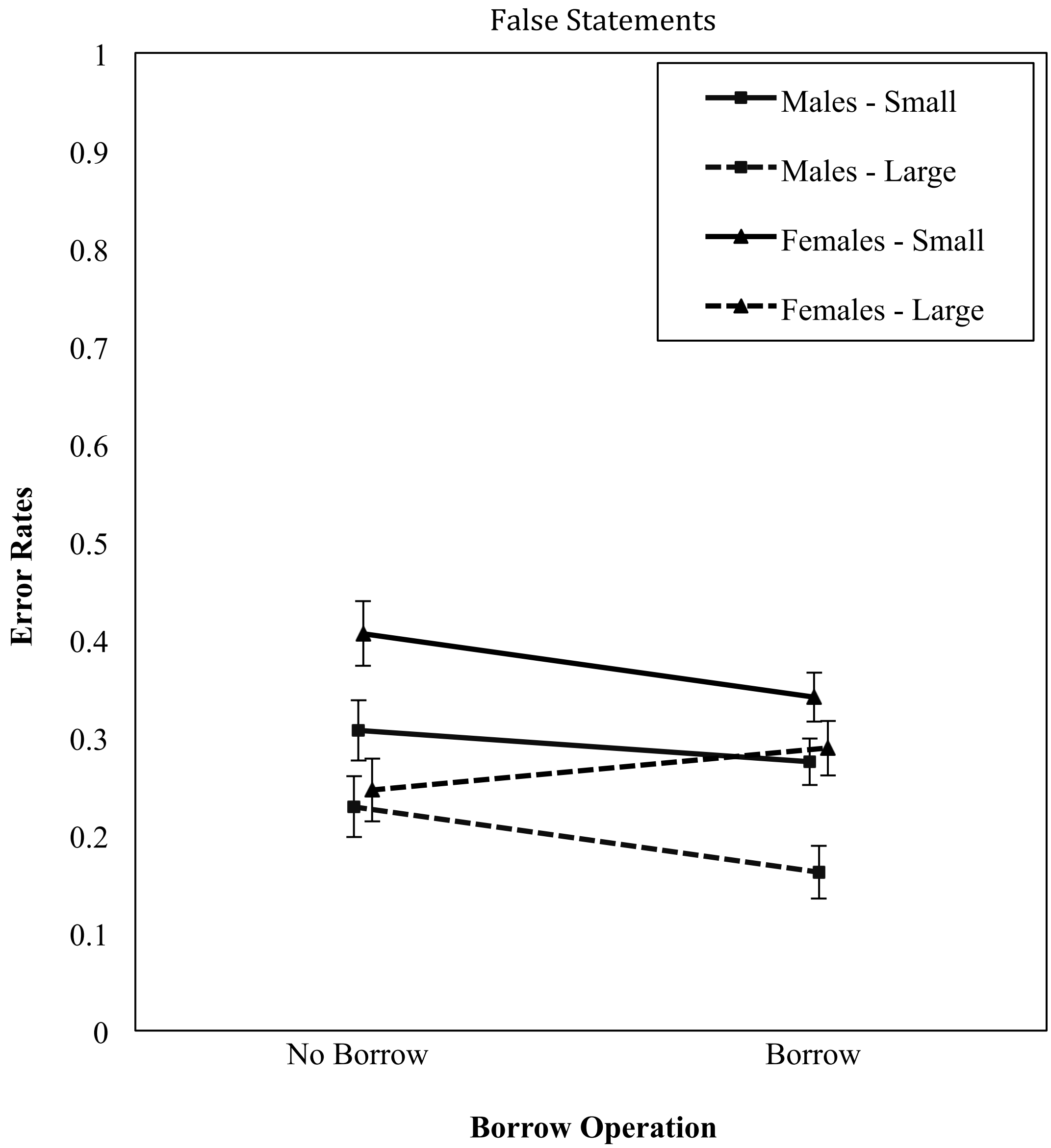

Figure 14: Error rates during the final test in Experiment 1 for gender, statement size, and borrow within the false condition. Solid lines signify small statements, dashed lines signify large statements. Error bars represent standard errors. Points are offset horizontally ro make error bars more visible.

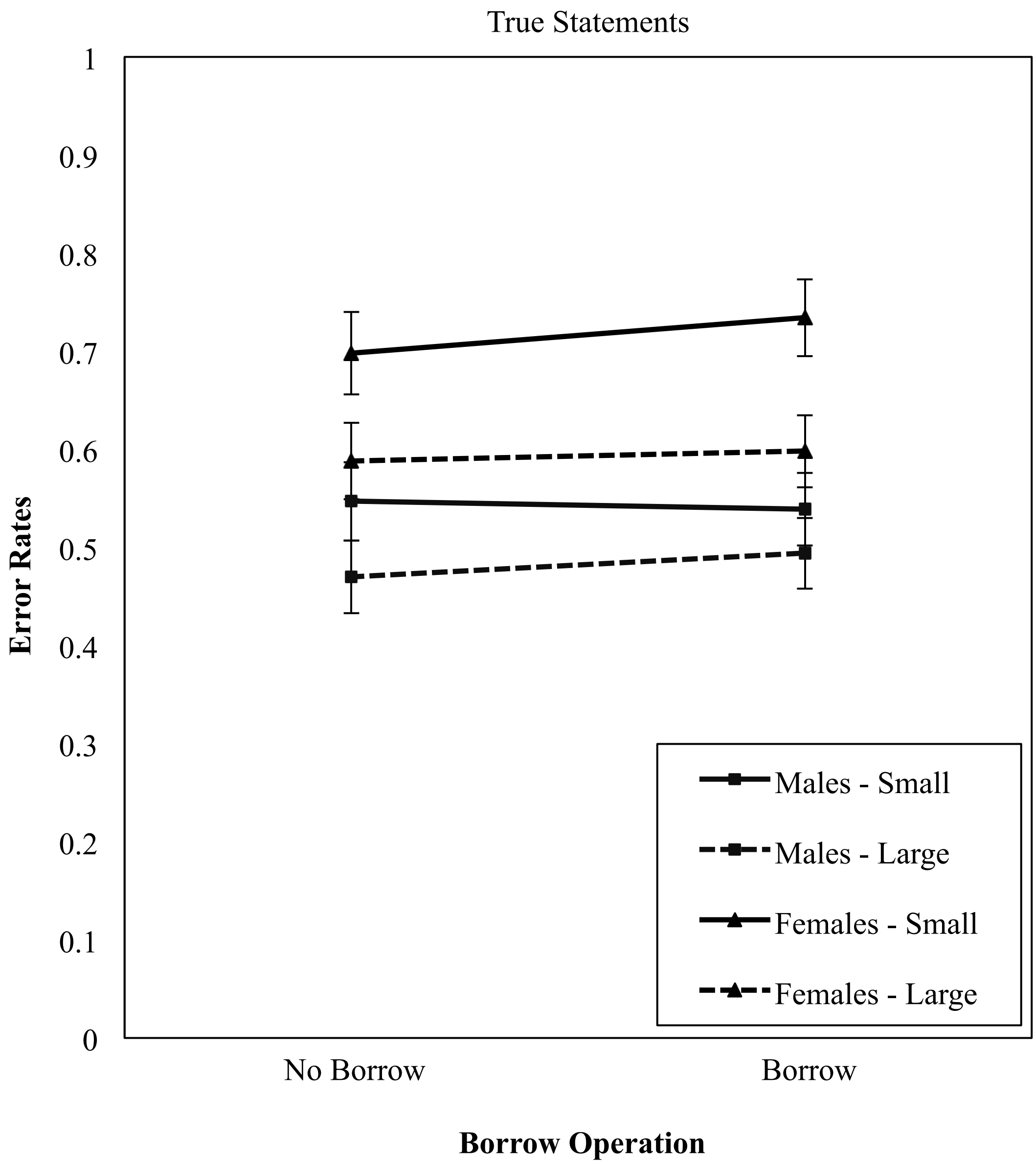

Figure 15: Error rates during the final test in Experiment 1 for gender, statement size, and borrow within the true condition. Solid lines signify small statements, dashed lines signify large statements. Error bars represent standard errors. Points are offset horizontally ro make error bars more visible.

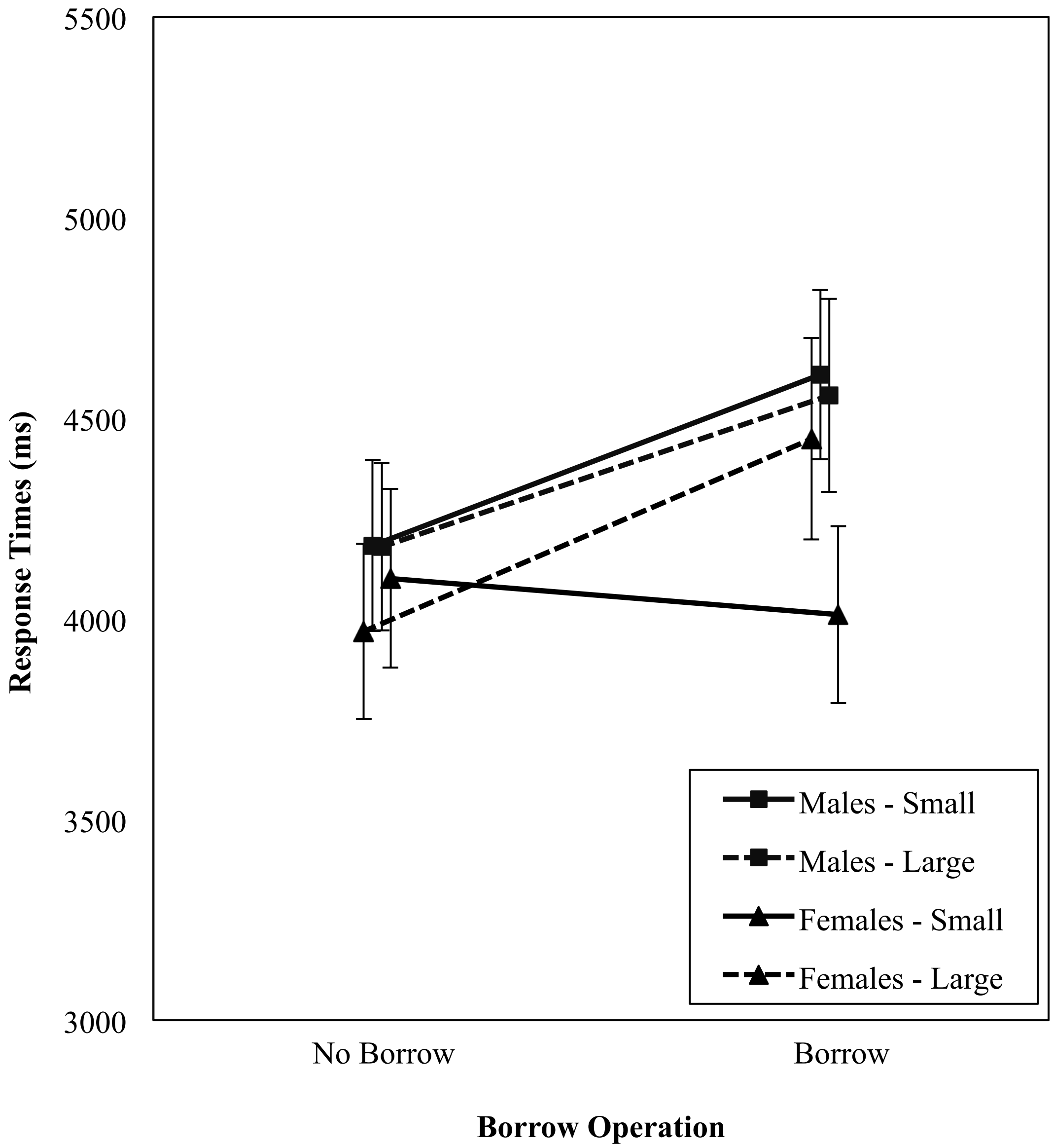

Figure 16: Response times during the final test in Experiment 1 for gender and within-subjects variables statement size and borrow. Solid lines signify small statements, dashed lines signify large statements. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

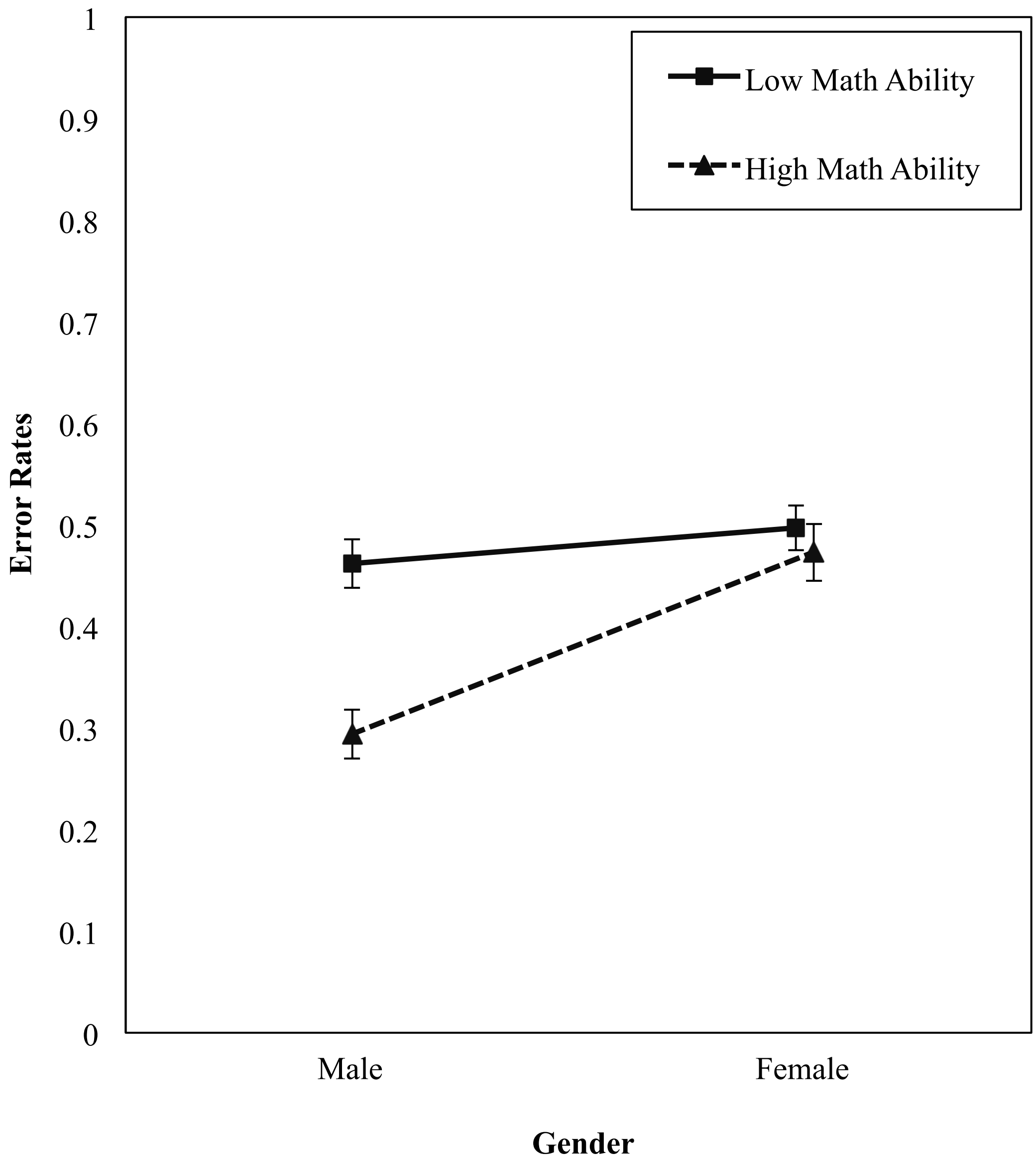

Figure 17: Error rates during the final test in Experiment 1 for gender and math ability. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

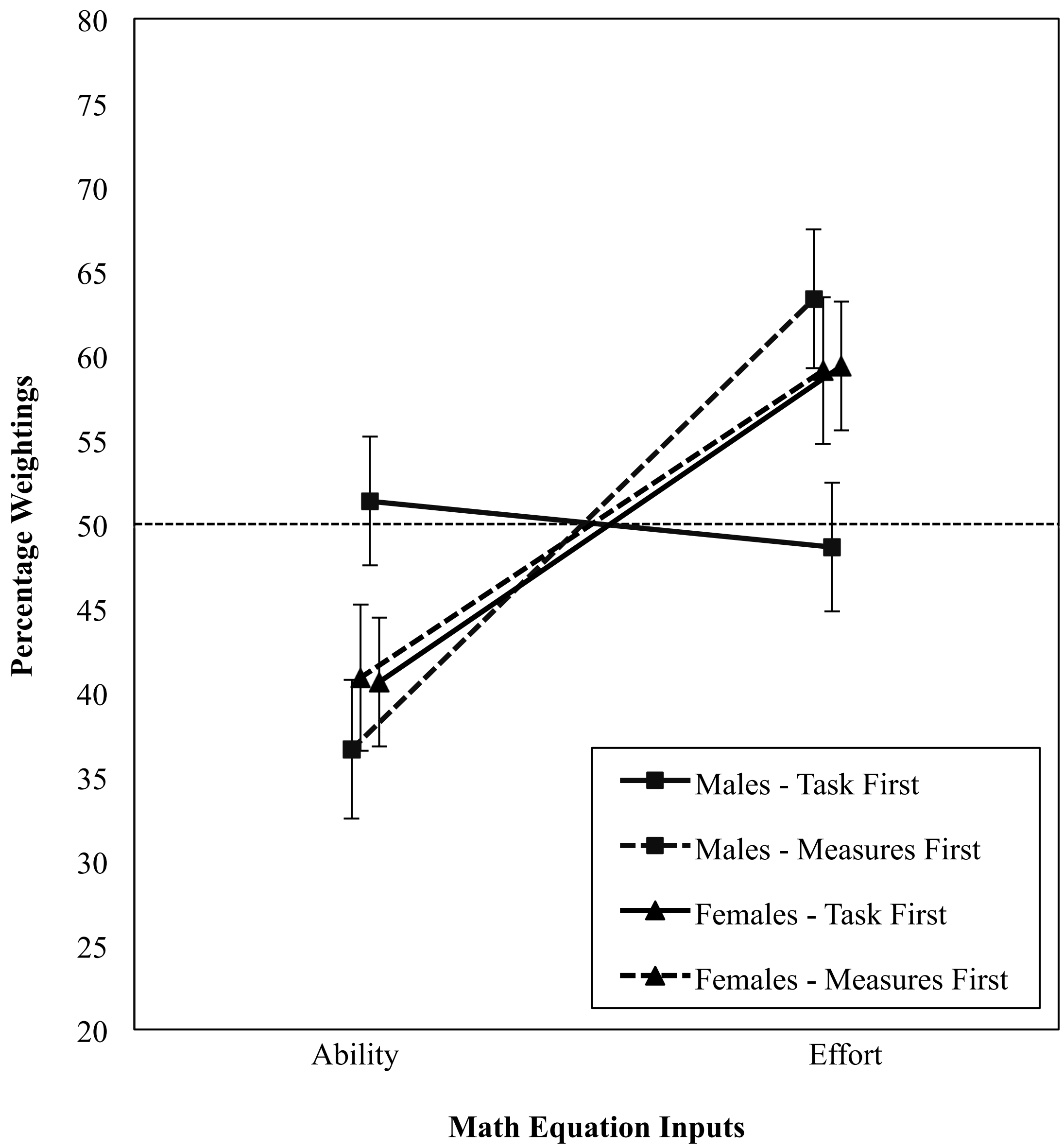

Figure 18: Weightings of ability and effort in the equation "Math intelligence = _____% effort + _____% ability" by gender and task order in Experiment 1. Dashed line at 50 represents equal weightings of ability and effort. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

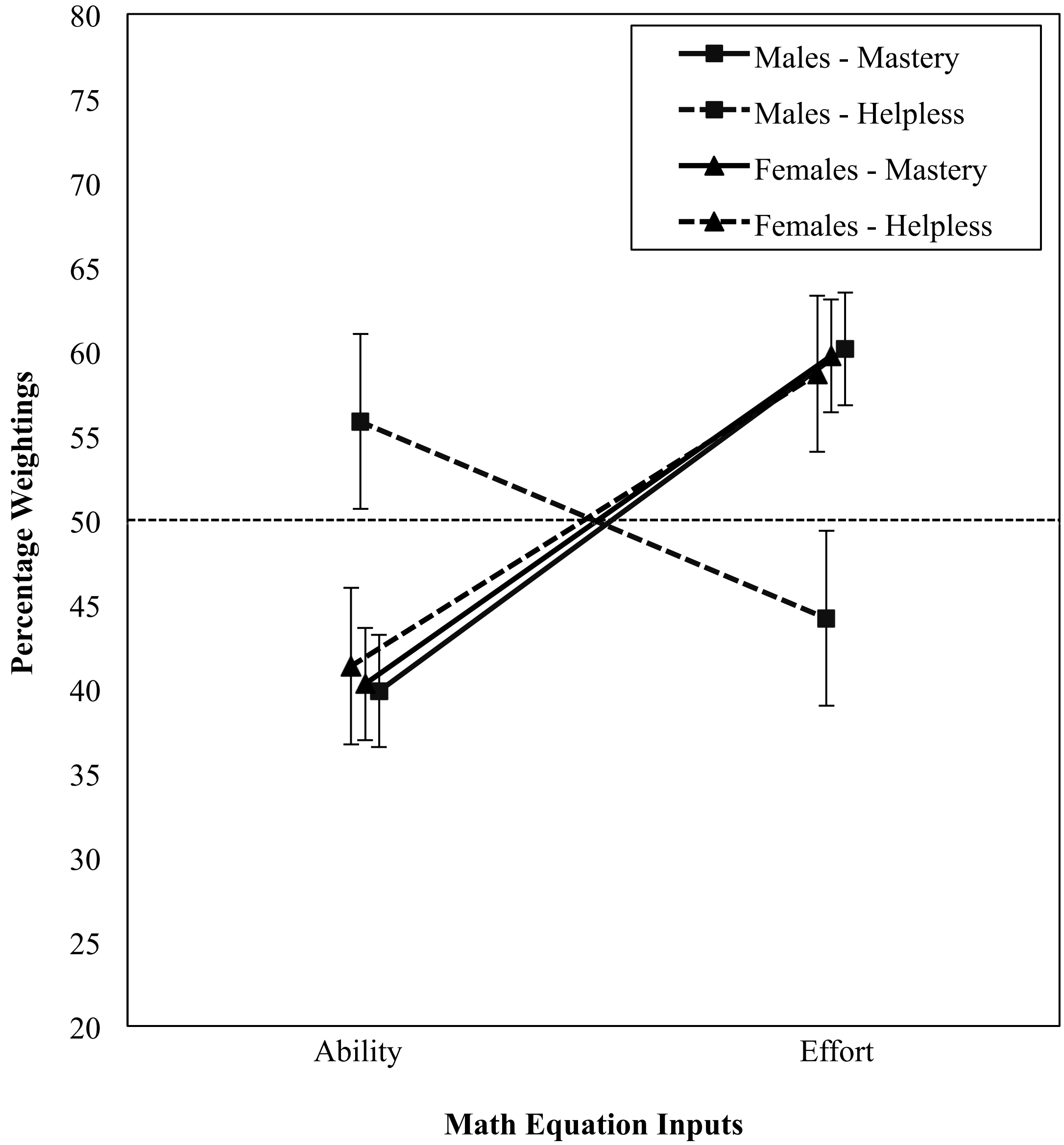

Figure 19: Weightings of ability and effort in the equation “Math intelligence = _____% effort + _____% ability” by gender and attributions to academic failure in Experiment 1. Dashed line at 50 represents equal weightings of ability and effort. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

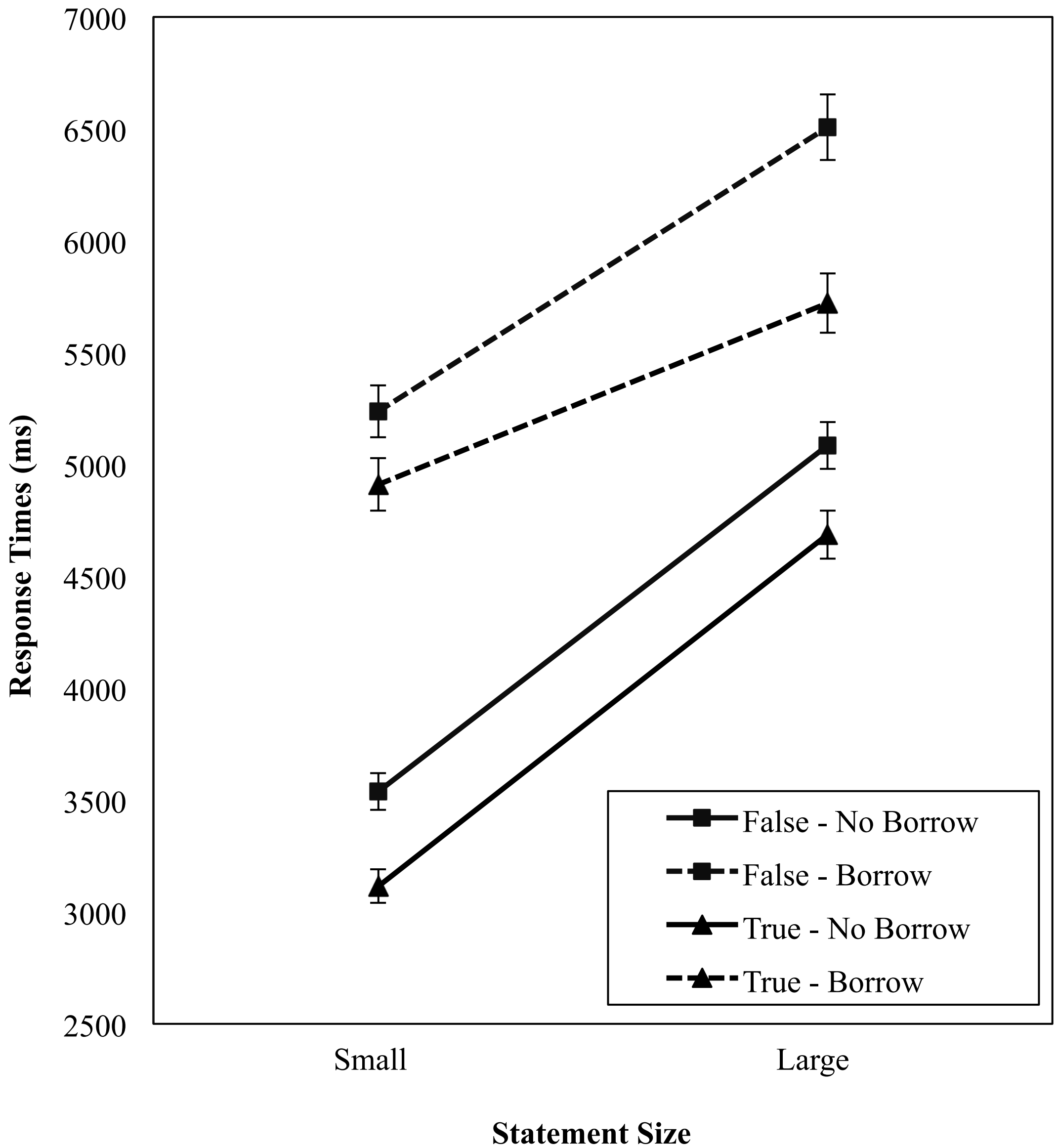

Figure 20: Response times during the final test in Experiment 2 for all three within-subjects variables true/false, statement size, and borrow. Error bars represent standard errors.

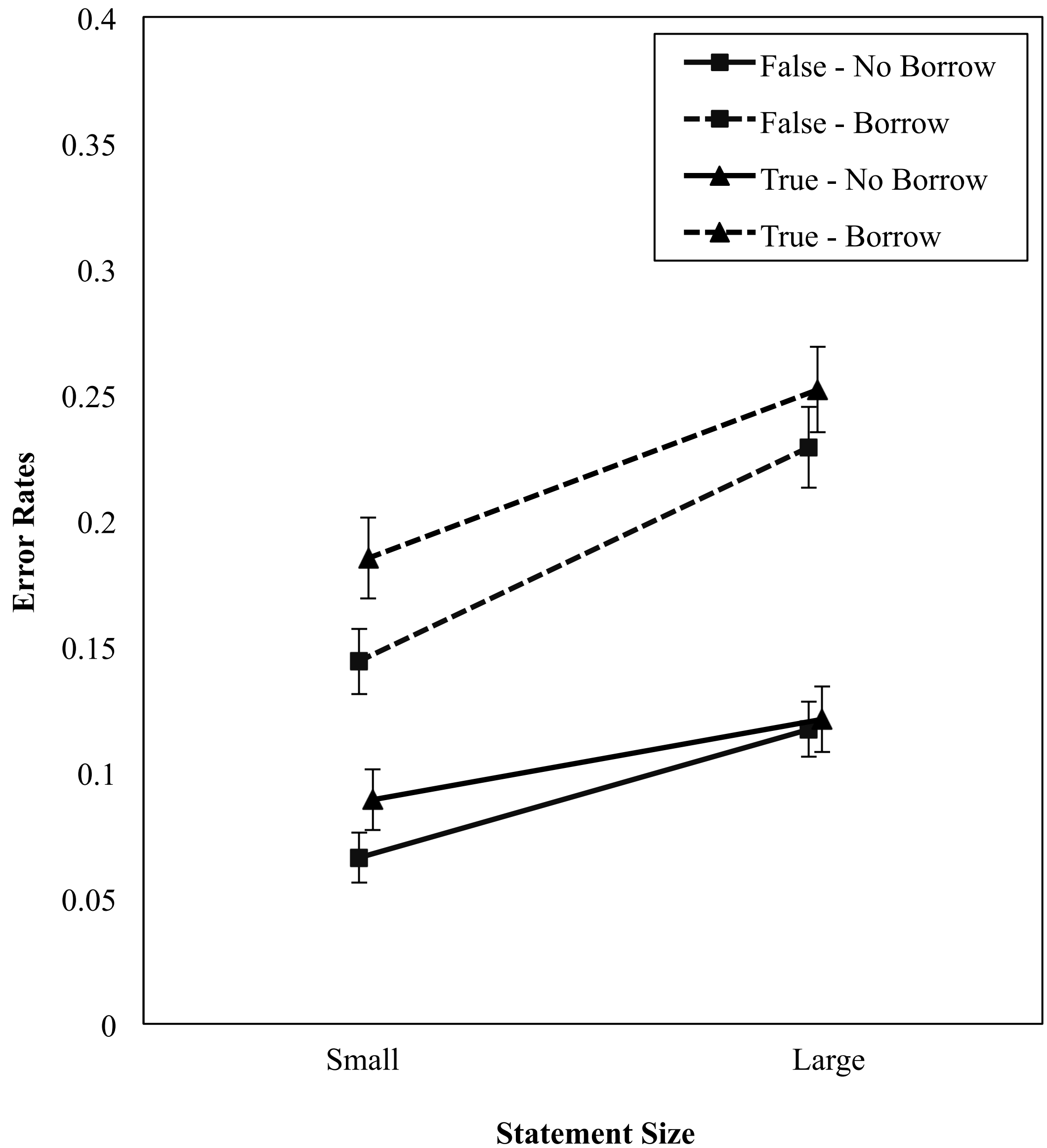

Figure 21: Error rates during the final test in Experiment 2 for all three within-subjects variables true/false, statement size, and borrow. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

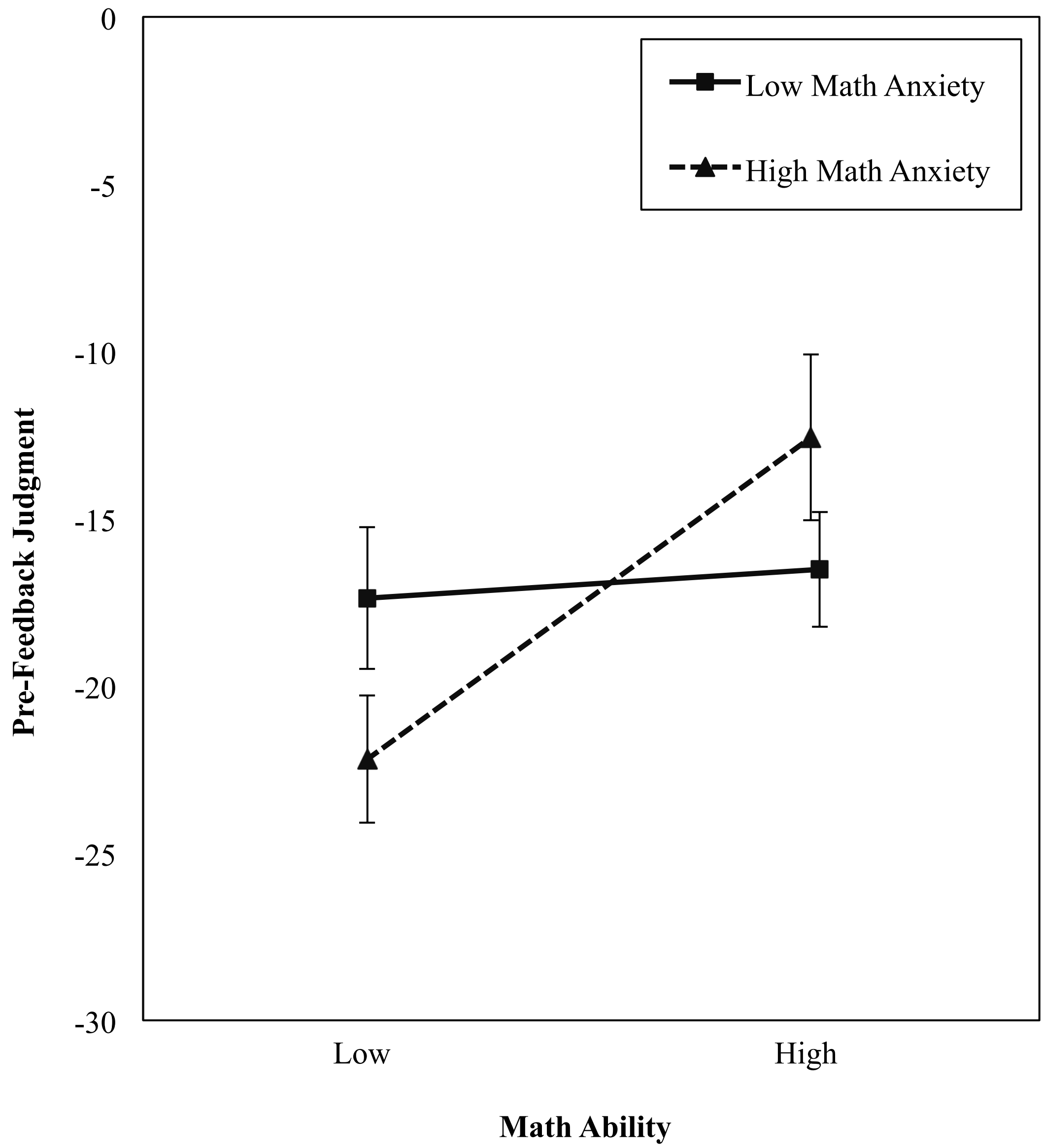

Figure 22: Participants' underestimates of their final test performance by math ability and math anxiety in Experiment 2. Zero represents accurately predicting their accuracy. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

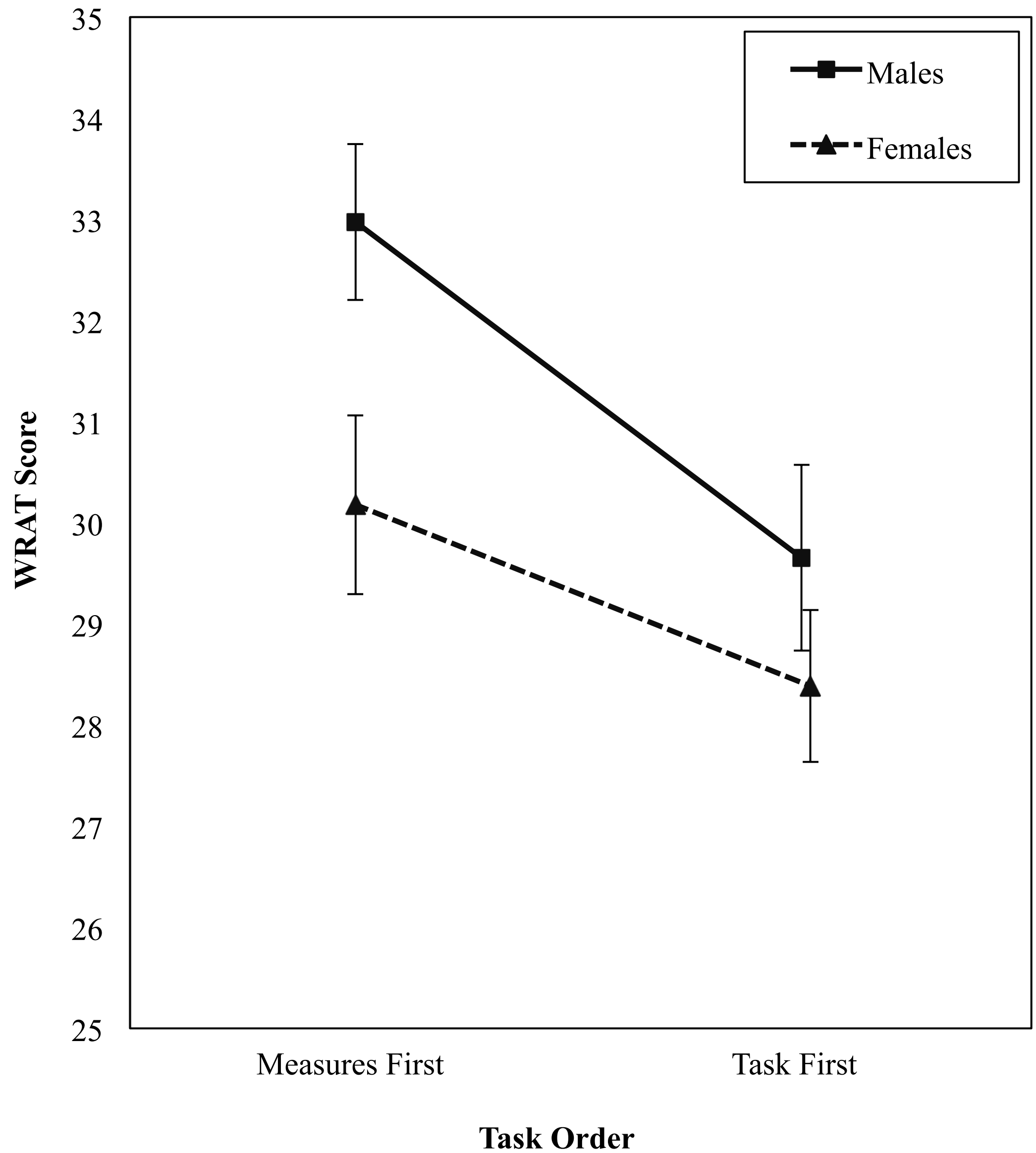

Figure 23: Measure of math ability in Experiment 2 of males and females taken either before or after the modular arithmetic task. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

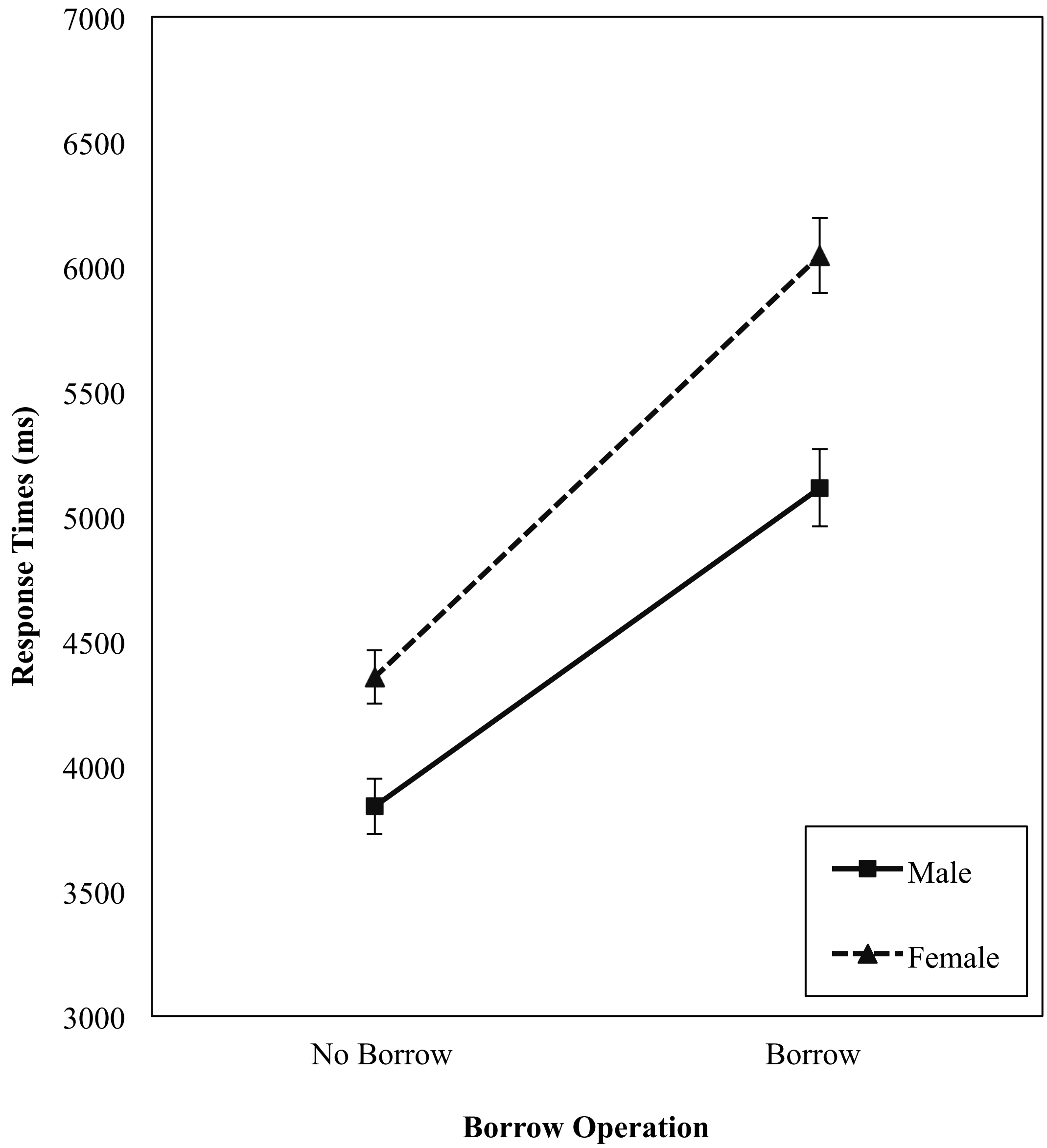

Figure 24: Response times during the final test in Experiment 2 for gender and borrow. Error bars represent standard errors.

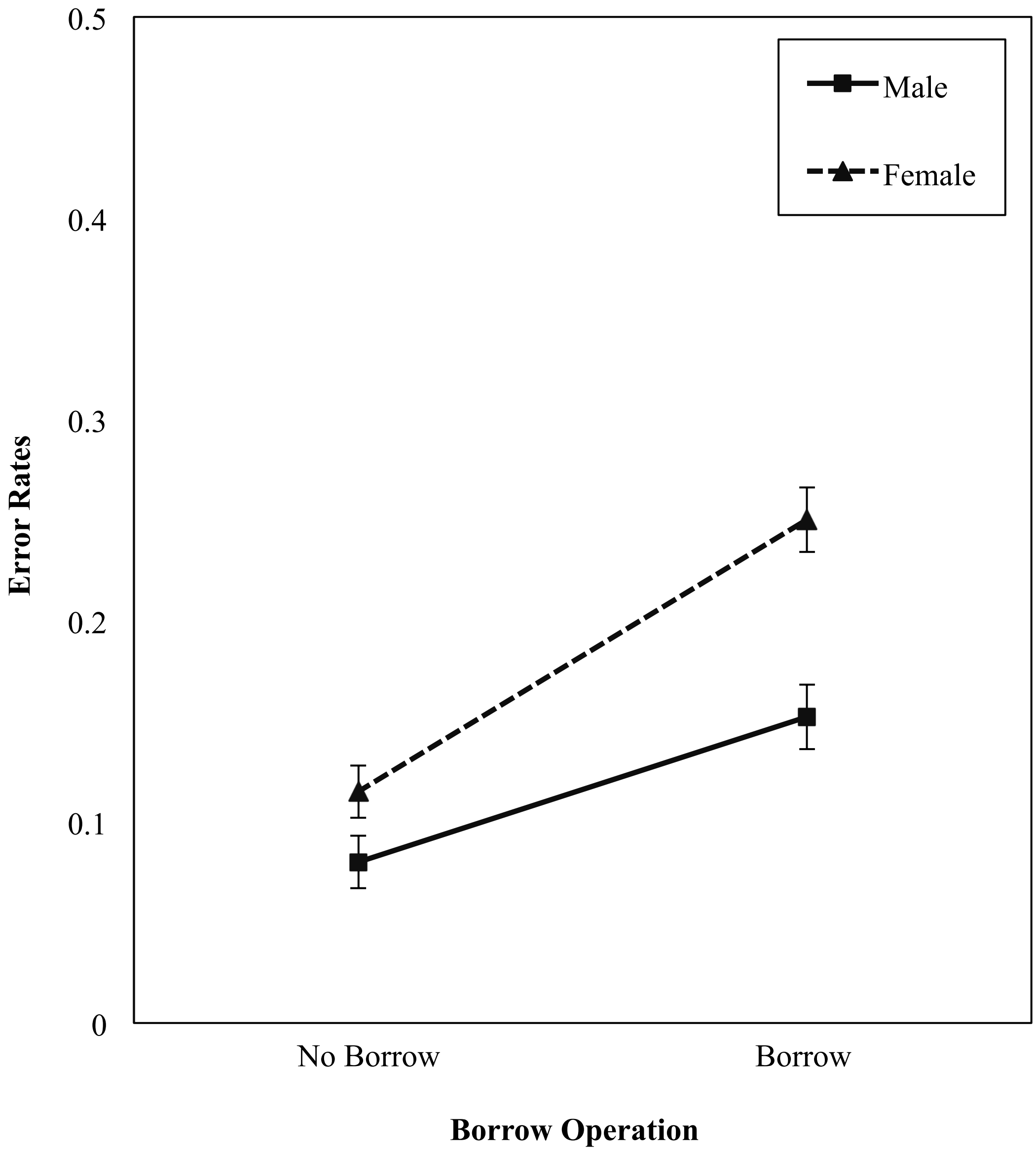

Figure 25: Error rates during the final test in Experiment 2 for gender and borrow. Error bars represent standard errors.

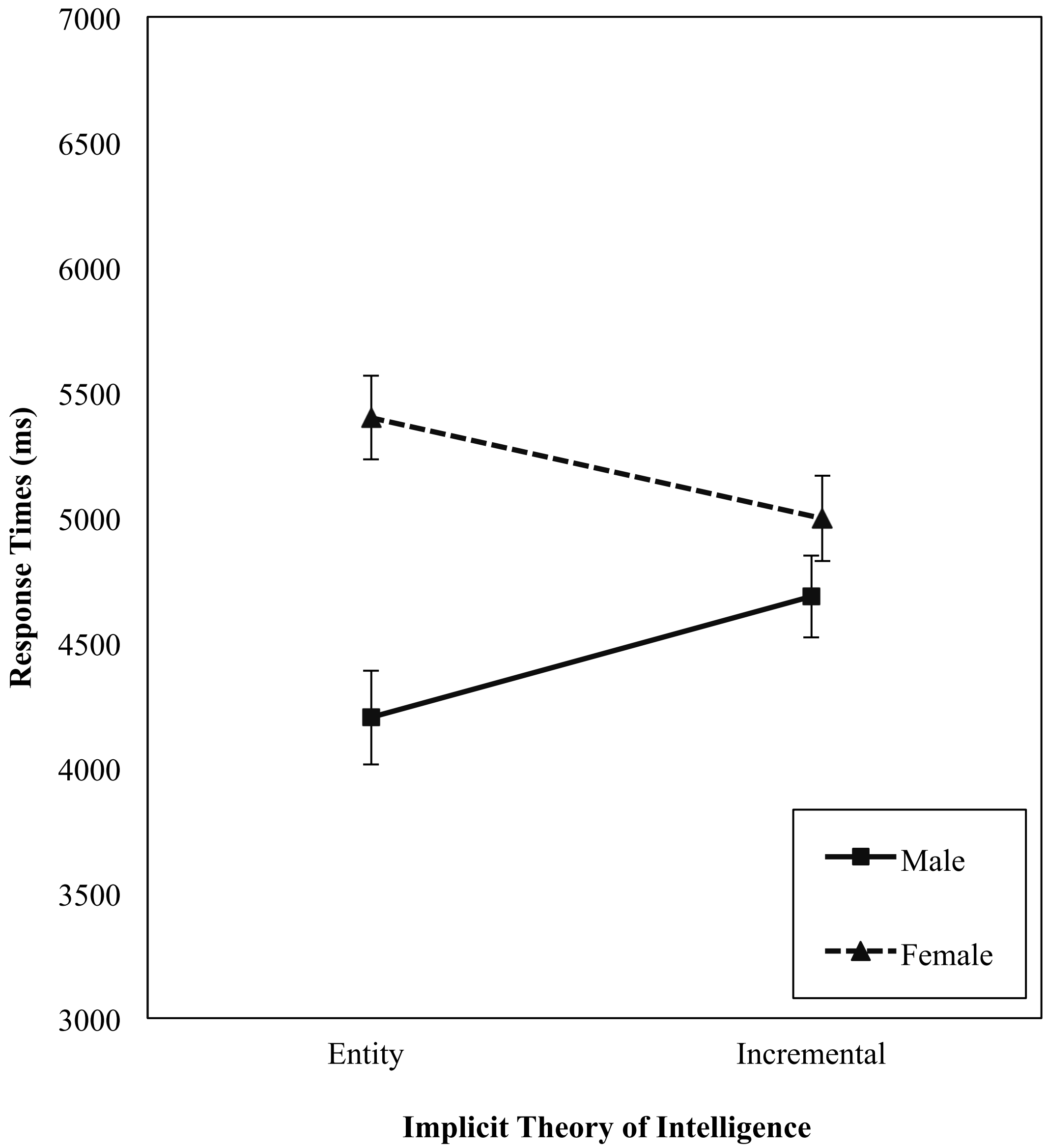

Figure 26: Response times during the final test in Experiment 2 for gender and implicit theory of intelligence. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

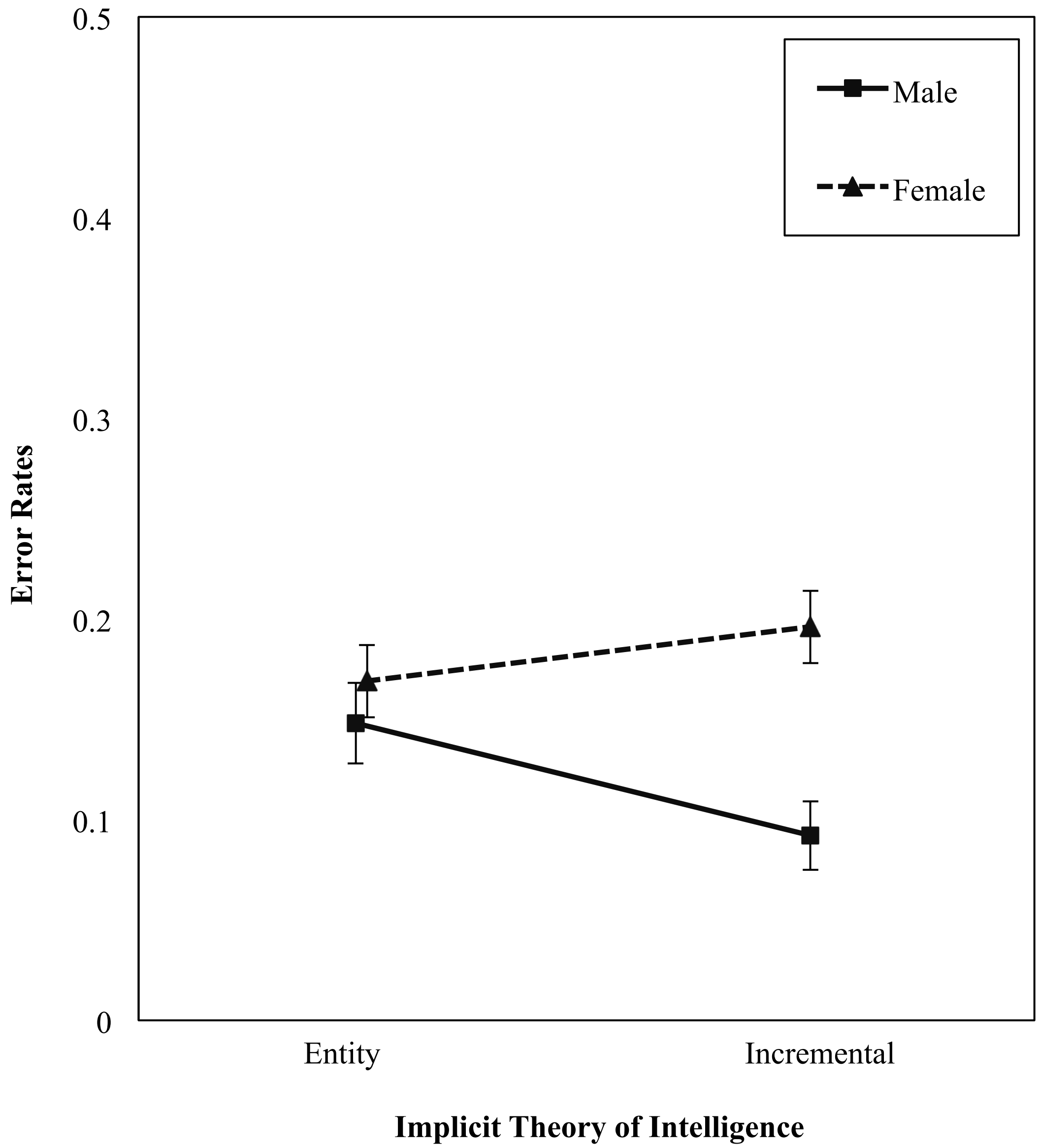

Figure 27: Error rates during the final test in Experiment 2 for gender and implicit theory of intelligence. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

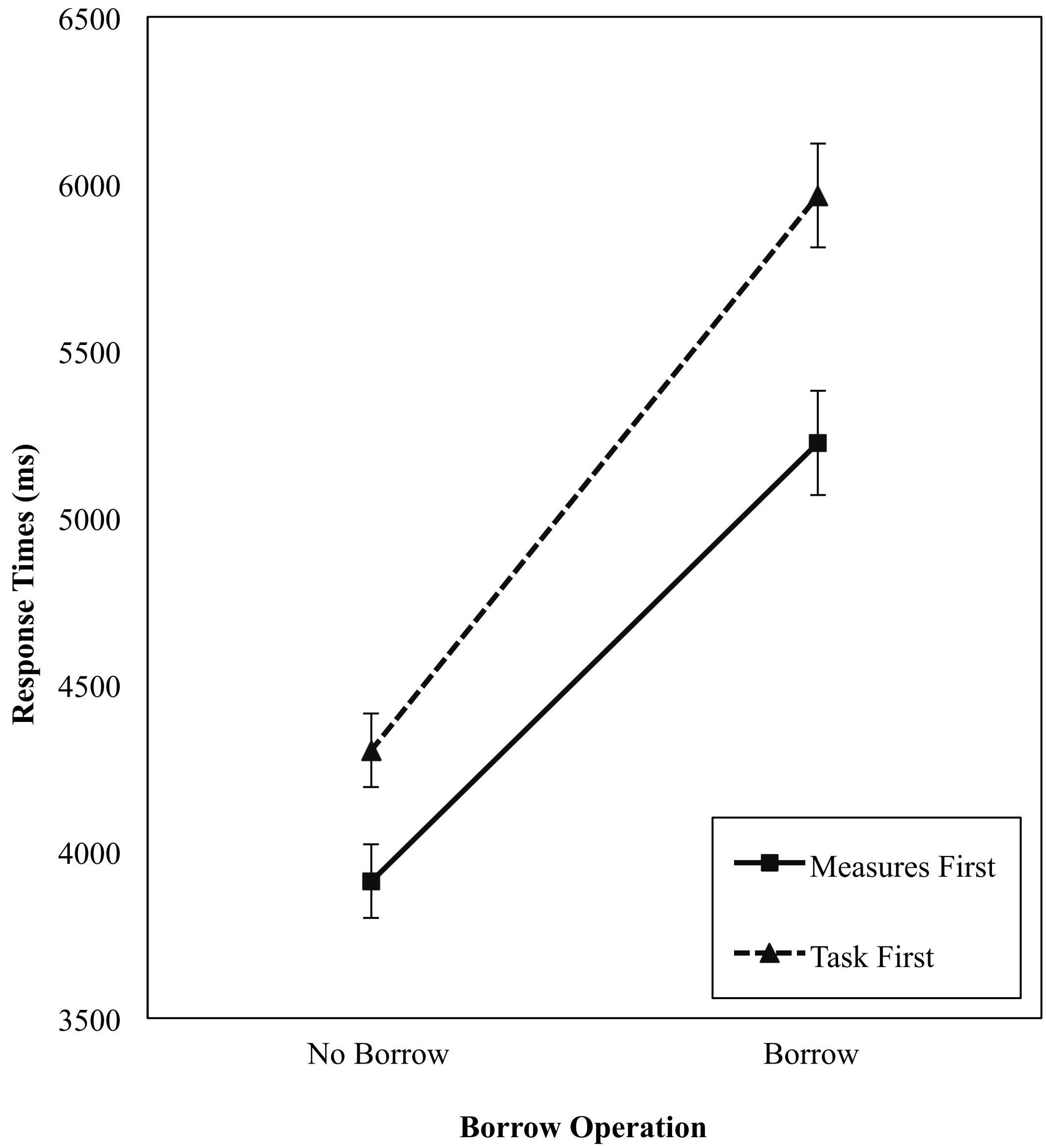

Figure 28: Response times during the final test in Experiment 2 for task order and borrow. Error bars represent standard errors.

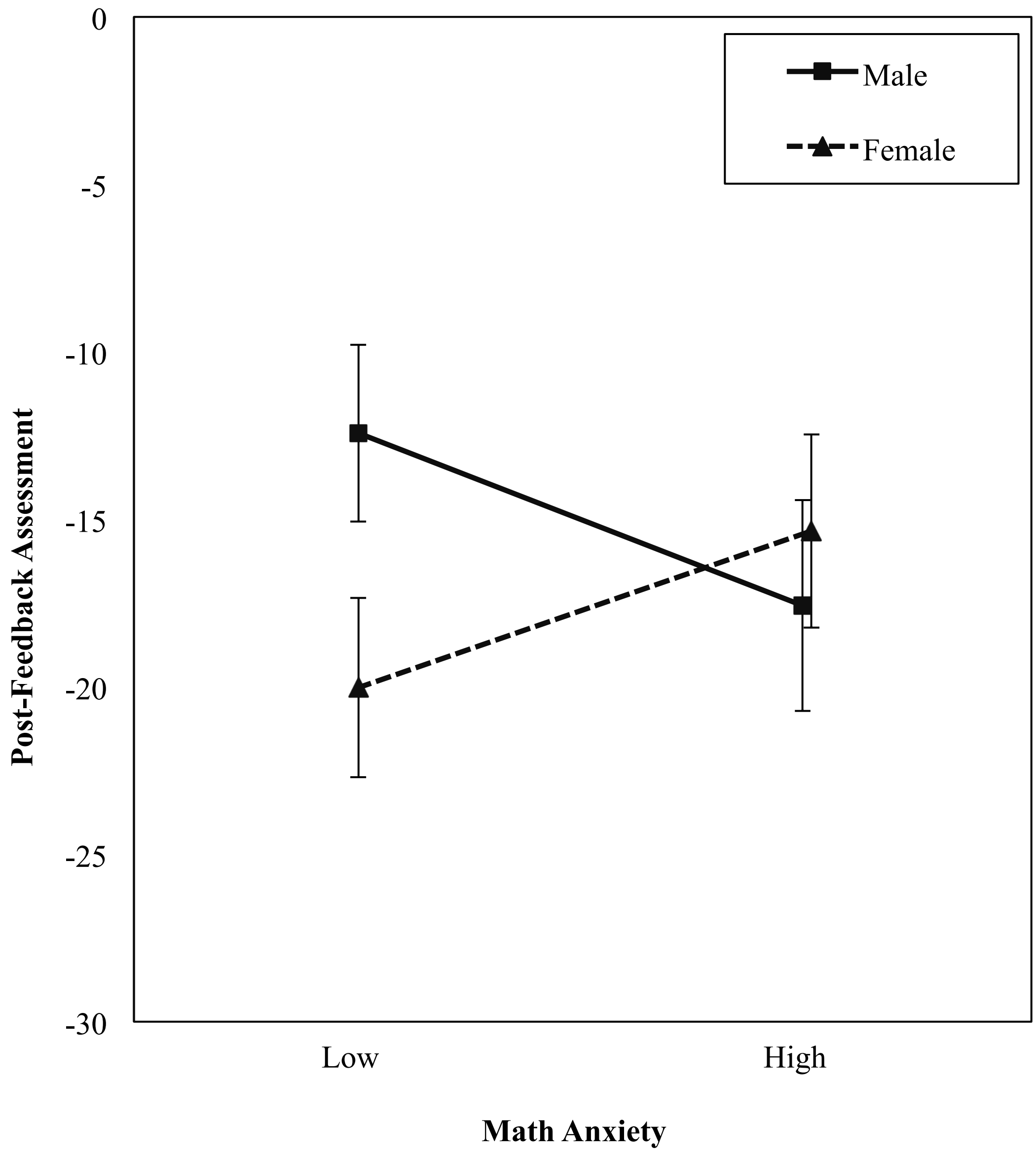

Figure 29: Participants' assessments of their final test performance by gender and math anxiety in Experiment 2. Negative values signify being less pleased than actual performance. Error bars represent standard errors. Points are offset horizontally to make error bars more visible.

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Education

M.A.	University of Nevada, Las Vegas Experimental Psychology Cognitive Emphasis	Summer 2014
B.S.	University of Nevada, Las Vegas Major: Mathematics Minor: Psychology	May 2009

Publications

Moore, M. A., **Rudig, N. O.**, Ashcraft, M. H. (2014) Affect, Motivation, Working Memory, and Mathematics. In Cohen, R., & Dowker, A. *The Oxford Handbook of Numerical Cognition.*

Ashcraft, M. H., & **Rudig, N. O.** (2012). Higher Cognition is Altered by Non-Cognitive Factors: How Affect Enhances and Disrupts Mathematics Performance in Adolescence and Young Adulthood. In Reyna, V. F., Chapman, S., Dougherty, M., & Confrey, J. *The Adolescent Brain: Learning, Reasoning, and Decision Making*. Washington, D. C.: APA.

Conference Presentations

Rudig, N. O. (2013, March) *Implicit Theories of Intelligence and Learning a Novel Mathematics Task.* Paper presented at the UNLV Graduate & Professional Student Research Forum, Las Vegas, NV.

Ashcraft, M. H., Moore, A. M., & **Rudig, N. O.** (2012, November). *Math Anxiety, Attitudes, Beliefs, and Performance.* Paper presented at the meetings of the Psychonomic Society, Minneapolis, MN.

Ashcraft, M. H., **Rudig, N. O.**, Moore, A. M., & Carr, T. H. (2012, November). *Attitudes about math and writing: Were you just "born" that way?* Poster presented at the meetings of the Psychonomic Society, Minneapolis, MN.

Bies-Hernandez, N. J., Copeland, D. E., **Rudig, N. O.**, Moore, A. M., & Ashcraft, M. H. (2012, November). *Examining the Benefits of Testing with Mathematical Learning.* Poster presented at the meetings of the Psychonomic Society, Minneapolis, MN.

Rudig, N. O. (2012, March) *Implicit Theories of Intelligence and Learning a Novel Mathematics Task.* Paper presented at the UNLV Psychology Graduate Research Fair, Las Vegas, NV.

Moore, A. M., **Rudig, N. O.**, & Ashcraft, M. H. (2011, November). *Calibrating Adults' Estimates in Dot Enumeration.* Paper presented at the meetings of the Psychonomic Society, Seattle, WA.

Rudig, N. O. (2011, March). *Spaced-Out Math: Order of Operations and Operand Spacing in Arithmetic Problems*. Paper presented at the UNLV Graduate & Professional Student Research Forum, Las Vegas, NV.

Rudig, N. O., & Ashcraft, M. H. (2010, November). *Spaced-Out Math: Order of Operations and Operand Spacing in Arithmetic Problems*. Paper presented at the meetings of the Psychonomic Society, St. Louis, MO.

Krause, J. A., **Rudig, N. O.**, & Ashcraft, M. H. (2009, November). *Math, Working Memory, and Math Anxiety Effects*. Poster presented at the meetings of the Psychonomic Society, Boston, MA.

Rudig, N. O., Durette, R. T., & Ashcraft, M. H. (2009, April). *Math Anxiety and Math Performance in Multi-Step Arithmetic Problems*. Poster presented at the meetings of the Western Psychological Association, Portland, OR.

Invited Talks

"Math Affect: A Cognitive Psychologist's Approach."
UNLV Academic Success Center,
Las Vegas, NV August 22, 2012.

"Math Affect: A Cognitive Psychologist's Approach."
UNLV Academic Success Center,
Las Vegas, NV August 17, 2011.

Honors and Awards

Graduate & Professional Student Association Funding

Fall 2010 - $550
Fall 2012 - $375
Psi Chi Merit Award: For supporting undergraduate involvement in Psi Chi

Professional Services

Experimental Student Committee

1st Year Cohort Representative	2009-2010
Interview Day Faculty Liaison	2010-2012
Vice-President	2012-2013

Teaching Experience

Instructor

Introduction to Psychology	Fall 2011, Spring 2012, Fall 2012, Spring 2013
Cognitive Psychology – Online	Fall 2013, Spring 2014

Graduate Assistant

History of Psychology	Fall 2009, Spring 2010
Perception	Fall 2009, Spring 2010
Abnormal Psychology	Fall 2009
Personality	Fall 2009
Statistics for Graduate Students	Fall 2010

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