MINDSETS AND MOTIVATION: MODELING PSYCHOLOGICAL DETERMINANTS OF ACHIEVEMENT IN THE POST-SECONDARY CLASSROOM

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ABSTRACT

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This dissertation expounded on Dweck's social-cognitive theory of mindsets and achievement motivation through the investigation of how college students operationalize mindsets as part of an intrapersonal attribution framework of motivation. The growth and fixed mindset frameworks suggest that students' implicit theories concerning the malleability of intelligence (i.e., their belief that intelligence is either something that is permanent or something that can be cultivated) shape divergent patterns of motivation that consequentially lead to varying achievement outcomes. While Dweck's motivational model of achievement has received considerable attention at the K-12 level, an empirical investigation of these causal links had yet to be considered at the collegiate level prior to this study. To determine whether mindsets influence the motivation and achievement of college and university students, a three-stage study was conducted utilizing a targeted and random sample of 2,000 first- and second-year students enrolled in introductory science, technology, engineering, and math (STEM) courses at a highly selective, public, research extensive university in the Mid-Atlantic. Responses from 501 participants to a self-administered survey, combined with demographic and academic information provided by the institution, composed the sample data set.

The initial stage-one analyses of this study considered whether the effects of mindsets on college students' motivation and academic achievement conformed to the specified parameters hypothesized in Dweck's original model. Structural equation modeling (SEM) – including confirmatory factor and latent variable path analyses – was

run to test and validate Dweck's conceptual model according to the sample. Results from the stage-one analyses suggest that while students do demonstrate various growth or fixed mindsets, these beliefs only serve as a proximal determinant of achievement strategies through the direct influence they have on effort beliefs and not, as hypothesized, through goal orientation. The inability to demonstrate a significant relationship between goal orientation and achievement strategies, coupled with inadequate measures of goodness-of-fit for the specified model, provides little evidence of the validity of Dweck's model at the postsecondary level.

Stage two of this study attempted to increase the absolute fit of Dweck's model while simultaneously providing an explanation of the spuriosity of the goal orientation factor. A hypothesized alternative model that appended measures of academic self-perception (operationalized as self-concept and self-efficacy in domain specific STEM courses) to Dweck's original model was estimated and tested. Path analysis results suggested that the hypothesized relationships are unable to improve the absolute fit of the model and therefore do not add to the explanatory power of Dweck's original specifications.

Finally, results from the stage-one and stage-two path analyses informed specifications for a modified model of mindsets and achievement motivation that retained many of the initial specifications of Dweck's conceptual model while excluding the goal-orientation construct. Goodness-of-fit and likelihood ratio tests for the stage-three path analysis provided significant grounds for recommending the modified model as the best tenable explanation of the effects of mindsets on college student achievement. The recommended model implies a direct causal influence of mindsets on students' belief in the utility of effort. These beliefs, in turn, influence the strategies students adopt in academic achievement scenarios, both directly and indirectly through the mediation of students' attributions for failure outcomes. Finally, the achievement strategies students adopt directly influence the end-of-course grades students received in introductory STEM courses.

Results from this study revealed that, although mindsets do influence achievement motivation at the post-secondary level, the implied causal influence of these psychological determinants does not conform to the specified parameters hypothesized in the motivation literature. These findings advance the understanding of the links between students' internal psychological processes and their academic achievement by providing empirical evidence regarding the true nature of mindset frameworks at the post-secondary level. Furthermore, these findings have the potential to improve faculty practice by offering instructors an avenue through which they can organize the pedagogy to leverage the influence of mindsets on motivation and achievement: a consideration that warrants further research. Though these findings are limited in their generalizability, results from this study provide strong support for attending to the psychological influences of motivation in the student learning narrative at the post-secondary level.

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APPROVAL OF THE DISSERTATION

This dissertation, "Mindsets and Motivation: Modeling Psychological Determinants of Achievement in the Post-secondary Classroom," has been approved by the Graduate Faculty of the Curry School of Education in partial fulfillment of the requirements for the degree of Doctor of Education.

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To my wife Holly
whose faith in me is relentless,
whose hope for me redoubles my motivation,
and whose love for me cannot be repaid.

I am forever grateful. 123

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CHAPTER 1

INTRODUCTION

With the publication of “From Teaching to Learning – A New Paradigm for Undergraduate Education” in 1995, Robert Barr and John Tagg directed the attention of administrators and scholars in the field of higher education to the importance of learning outcomes. The article came at a time of rapid transition for U.S. colleges and universities: the recession of 1990-91 required states to shift limited appropriations to other public services (health, corrections, K-12 education), constituting a significant disinvestment in public institutions of higher education; America’s diminished gross domestic product called into question the benefits of a post-secondary degree, compelling college and university accreditors to strengthen the rigor of program evaluation; and a marked increase in federal need-based scholarships and grants forced educators to consider new ways of reaching an increasingly diverse population of students. In short, these compounding external forces coupled with calls for accountability demanded that colleges and universities reexamine the foundational purposes of higher education. “A paradigm shift is taking hold in American higher education” Barr and Tagg wrote. “In its briefest form, the paradigm that has governed our colleges is this: A college is an institution that exists to provide instruction. Subtly but profoundly we are shifting to a new paradigm: A college is an institution that exists to produce learning. This shift changes everything” (p. 13).

"From Teaching to Learning" described in detail the need and rational for colleges and universities to reinvest in the student learning process. For Barr and Tagg (1995), the benefits of a new *learner-centered* approach to teaching far outweighed those of the existing *instruction-centered* paradigm. The instruction-centered paradigm had dominated the field of higher education since the incorporation of Harvard in 1636, whereby instructors' pedagogical approaches (e.g., lecture and oratory) cast the instructor as the most important agent in the college classroom (Tagg, 2003). Knowledge, in this paradigm, is dispensed by the instructor and retained by the student. Student achievement in the instruction-centered paradigm is then measured as the student's ability to prove that he or she has retained this information (Barr & Tagg, 1995). A shift to the *learner-centered* paradigm integrates the student into the fabric of the learning process. Knowledge, in this paradigm, is co-constructed by students in an environment facilitated by the instructor. Student achievement in the learner-centered paradigm is criterion based (i.e., dependent on student mastery of learning outcomes according to pre-determined performance levels). While couched in econometric terms such as "cost-benefit" and "productivity," a distillation of Barr and Tagg's (1995) central argument suggests student outcomes are considerably better when student learning is emphasized over content recitation. They argued that by shifting to the learner-centered paradigm, colleges and universities could produce more complex or higher-order learning outcomes to meet the cries of accountability from college and university stakeholders.

Nearly two decades after "From Teaching to Learning" was published, a report from the Higher Education Research Institute at UCLA (Eagan et al., 2014) has suggested that indeed, professors are overwhelmingly adopting learner-centered pedagogical approaches in their teaching. Data from the organization's 2013-14 Faculty Survey indicates that over 80 percent of faculty report that they incorporate class discussions in most or all of their courses, compared to nearly 70 percent in 1990. Most notably, rates of faculty reliance upon group projects and cooperative learning have more than doubled during the same 25 years, from 18 and 26 percent in 1990 to 46 and 61 percent in 2014 respectively. This dramatic shift towards a learner-centered classroom is staggering. Consequentially, the responsibility for learning in the classroom is swiftly pivoting from the instructor to the student – that is, the quality of student interaction in the classroom, now more than ever, drives academic achievement (Bain, 2011; Fink, 2013).

To better understand the relationship between individual student interaction and academic achievement at the college-level, the *scholarship of teaching and learning* (SOTL) has traditionally focused on two interrelated areas: pedagogy and student engagement (Hutchings, Huber, & Ciccone, 2011). The importance of using high quality, learner-centered pedagogy (e.g., Socratic method, case studies, problem-based learning) to promote learning is well documented (see Ambrose, Bridges, DiPietro, Lovett & Norman, 2010; Bain, 2011; Fink, 2013). Modest learning gains have been demonstrated by the adoption of these teaching practices in fields such as science, technology, engineering, and math (STEM) (see Mastascusa, Snyder & Hoyt, 2011), the social sciences (Oakley, 2002; Fox, 2003), and the humanities (see Perry & Smart, 2007). Similarly, it is well understood that students who actively engage with course material are more likely to succeed academically (Astin, 1993; Barkley, 2010; Kuh, Kinzie, Schuh & Whitt, 2005). That students learn more and retain their understanding longer as a result of increased engagement in the learning process is well documented (e.g., Barkley, 2010; Bean, 1996; Donovan, Bransford,& Pellegrino, 1999).

While these lines of inquiry continue to provide a deep understanding of how college environments affect student learning outcomes, there remains a considerable deficit in contemporary SOTL efforts to understand student psychological approaches to learning opportunities (McKeachie, Pintrich, Lin, Smith & Sharma, 1994; McKinney, 2004). Ignoring such a prominent piece of the student learning equation assumes that all college students expect the same achievement outcomes and value learning in the same ways. Moreover, such an approach fails to attend to the intrinsic motivational variables that encourage student learning. This is concerning, given that student success in the learning-centered paradigm relies so heavily on the initial motivation of students as they approach learning opportunities (Graham & Williams, 2010; Svinicki, 2004).

According to Weiner's (1986) systems of attribution motivation, students' previous academic experiences drive them to predict future academic outcomes. These predictions, in turn, motivate the students to engage in productive academic strategies (e.g., participation in class, completion of homework, studying) (Covington, 2000; Wiener, 1986). Every student has a different perception of his or her past achievement. Accordingly, each student has a different motivational approach to the academic opportunities he or she encounters. Weiner (1986) proposed that students form these psychological approaches to learning as a result of two qualitatively different yet interdependent systems: the intrapersonal and interpersonal systems of motivational development. The intrapersonal system of motivational development provides a framework for why individuals engage in activities apart from the influence of other people or environments. While Weiner acknowledged that people derive motivation for their actions as a result of relationships (i.e., interpersonal motivation), his research demonstrated that individuals are just as likely to engage in behavior as a result of an internally analytical process. Weiner's theory therefore suggests that students approach learning opportunities with an internal framework of motivation that is unassociated with the quality of classroom instruction. This then presents a number of complex questions for scholars in the field of teaching and learning: what qualities or characteristics shape the intrapersonal motivation of students in the collegiate classroom, and in turn, how does student motivation influence academic achievement apart from the environmental factors of the college classroom?

The Role of Mindset in Motivation and Achievement

It is questions similar to these that have inspired a number of social psychologists to investigate the links between motivation and achievement. In particular, Stanford Professor Carol Dweck's (1999; 2006) work in the social-cognitive field of self-beliefs and achievement motivation led her to conclude that in order for students to be motivated to succeed academically, they must first believe that success is possible. According to Dweck (1999), self-theories (i.e., the beliefs people have about themselves) profoundly affect the interpretation of life's events by serving as psychological schemas that influence decision-making and significantly affect how students engage the academic setting. Maybe most notably, Dweck (1999; 2006) suggested that the implicit beliefs students have about the nature of intelligence – that is, whether or not intelligence is a static or plastic quality – provides a framework for motivation and academic achievement. In her early work, Dweck (see Dweck, 1999; Dweck, Chiu, & Hong, 1995;

Dweck & Leggett, 1988) referred to these beliefs as *implicit theories of intelligence*, or the unconscious "theory" (i.e., belief) in the malleability of intelligence. In subsequent studies, Dweck (see Dweck, 2006; Yeager & Dweck, 2012) has gravitated to describing these self-beliefs as *mindsets*, noting that these implicit beliefs form divergent frameworks that affect motivation and achievement in different ways.

Student mindsets fall along a spectrum from a fully *fixed mindset* to a fully *growth mindset*. For some students, their implicit beliefs about the nature of intelligence presume that intelligence is a "fixed," static quality that does not change (Dweck, 1999; Dweck & Leggett, 1988). Dweck (1999) suggests that these students believe in an *entity theory* of intelligence: that is, people are born with a fixed amount of intelligence, and there is nothing that can be done to change the amount of this "entity." Other students believe that intelligence can be "grown" or cultivated in "increments." Sometimes labeled *incremental theorists*, these growth mindset students hold implicit beliefs that suppose intelligence is a malleable quality that can be nurtured through applied effort (Dweck & Leggett, 1988).

According to Dweck and Leggett (1988), these contrasting mindsets shape how students approach learning opportunities. Students with a fixed mindset, who believe intelligence is a quality to be demonstrated rather than cultivated, place a great deal of faith in their abilities. When challenged, these students devise strategies to help demonstrate their ability and attribute their successes and failures to their performed ability (or inability). Growth mindsets promote a different approach to learning. Students who believe intelligence can be cultivated tend to rely on applied effort to increase their intelligence rather than prove their current ability.

Mindsets are apparent in a number of different intelligence domains including the interpersonal, kinesthetic, and academic domains (Dweck, 2006). While Dweck (2006) admits that students can fall along a spectrum ranging from a full-fixed mindset to a full-growth mindset, research (Dweck, Chiu, & Hong, 1995) demonstrates that in the academic domain, nearly 85 percent of students exhibit either a growth *or* fixed mindset. In light of this evidence, student mindsets may provide an optimal starting point for understanding how students frame their academic experience to predict their future academic outcomes--processes that are foundational in the intrapersonal motivation of college students (Weiner, 1986).

Dweck's (1999) Conceptual Model of Motivation and Achievement

Observations concerning the nature of mindsets and the relationships they share with motivational variables such as goal orientation and effort attribution have led Dweck and her colleagues to propose a conceptual model of achievement motivation (Dweck, 1999; Dweck & Leggett, 1988; Dweck & Sorich, 1999). In this model, students' implicit theories of intelligence, or mindsets, play a causal role in student motivation and academic achievement. Research (Blackwell, Trzesniewski, & Dweck, 2007; Henderson & Dweck, 1990) has demonstrated that students with comparable intelligence respond to academically challenging situations in different manners based on their academic mindset. Conceptually, Dweck's (1999) motivational model of achievement proposes two divergent paths of academic motivation that begin with mindsets and end with different achievement outcomes (see Figure 1). In comparison to students with a fixed mindset, students with a growth mindset (a) subscribe to mastery/learning goals rather than performance goals (Dweck & Leggett, 1988; Grant & Dweck, 2003); (b) believe effort is a useful tool for achievement in situations that prove difficult or beyond the student's ability (Aronson, Fried, & Good, 2002; Hong, Chiu, Dweck, Lin, & Wan, 1999); (c) attribute failures to a lack of effort rather than a lack of ability (Henderson & Dweck, 1990; Stipek & Gralinski, 1996); and (d) display mastery-oriented strategies (e.g., studying, time-management) rather than helpless response patterns (e.g., procrastination, absenteeism) (Dweck & Sorich, 1999; Robins & Pals, 2002). In light of this evidence, Dweck (1999) hypothesized that implicit theories of intelligence create entirely distinct psychosocial schemas for applying motivation to achievement opportunities, each having measurable effects on achievement outcomes.

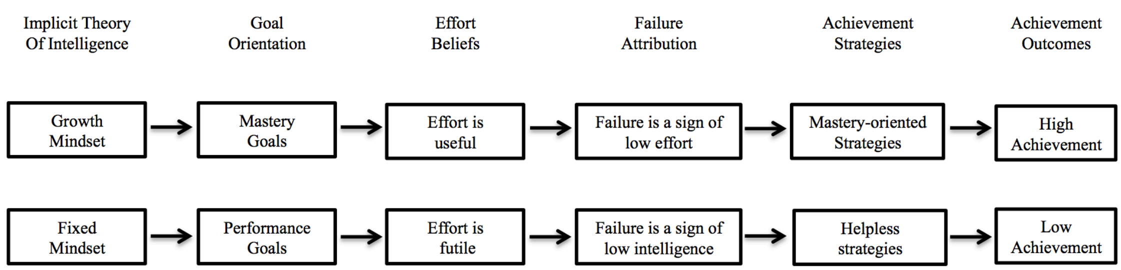

Figure 1. Conceptual image of Dweck's (1999) motivational model of achievement representing divergent paths of fixed and growth mindset students in academic achievement.

To test Dweck's hypothesis that mindsets influence motivation and play a causal role in academic achievement, Blackwell, Trzesniewski, and Dweck (2007) gathered data from a longitudinal field study of students in the transition from sixth to seventh grade. Participants in the study were all members of a cohort of students facing the academic challenge of new course material and a new academic environment as they entered junior high school. The data gathered from these students measured the motivational variables of mindsets, achievement goal orientations, effort beliefs, failure attributions, and achievement strategies along with baseline and outcome achievement scores (operationalized as scores on both sixth and seventh-grade standardized mathematics achievement tests). To better understand the causal relationships between these factors, Blackwell and her colleagues employed both exploratory factor analysis and latent variable path analysis. Their results indicated that while the students' mindsets and other motivational variables were uncorrelated with prior academic achievement, each played a significant role in the motivation and achievement gains of students as they passed from sixth- to seventh-grades. Though these effects were measured at the junior high school level, Dweck (2006; Grant & Dweck, 2003) has hypothesized that implicit theories of intelligence may play a similar role in the motivation of college students as they engage in new and challenging coursework at the post-secondary level.

Mindsets at the Collegiate Level

Although the influence of student mindsets and other various aspects of Dweck's (1999) motivational model of achievement have received significant attention in both elementary and secondary education (see Dweck, 1999; 2006), few studies have explored these relationships at the post-secondary level. Of the research that has been conducted, the findings vary widely. Curry, Da Fonseca, Zahn, and Elliot (2008) found that college students with fixed mindsets often demonstrate more levels of anxiety over their performance when compared to those with growth mindsets. Nussbaum & Dweck (2008) observed that when receiving feedback on an assignment in which a student performed poorly, students with fixed mindsets were more likely to seek out downward comparison strategies (e.., comparing their failure to students who performed worse on the same assignment), while students with growth mindsets were more likely to seek out examples from those students who scored better than they did on the assignment (i.e., upward comparison). Similarly, Hong and his colleagues (1999) revealed that college students with growth mindsets are more likely to seek out remedial help when faced with challenges in comparison with students who embody a fixed mindset.

At the collegiate level, students' implicit beliefs about the nature of intelligence, without intervention, remain relatively consistent in college, both over brief periods of time (e.g., one semester) (Grant & Dweck, 2003) and throughout the duration of the traditional four years of study (Robins & Pals, 2002). At the same time, interventions designed to manipulate student mindsets in controlled studies have demonstrated some efficacy at the post-secondary level (Aronson et al., 2002; Chiu, Hong, & Dweck, 1997). In these studies, college students who participated in an intervention specifically designed to encourage incremental theories of intelligence were more likely to adopt stronger growth mindsets than those students who did not participate in the intervention.

While the aforementioned studies demonstrate various roles that mindsets play in college academic achievement, they only hint at a tenable explanation for how mindsets are operationalized in achievement motivation. Other studies (e.g., Aronson et al., 2002; Hong et al., 1999;) have demonstrated that relationships between student mindsets and academic achievement do exist at the college level, yet no study has sought to empirically assess Dweck's (1999) conceptual framework of mindsets, motivation, and achievement at the post-secondary level in its entirety.

Purpose

Efforts over the past 20 years to investigate student learning have provided significant insight regarding the influences of classroom environments on student achievement, yet the scholarship of teaching and learning has often overlooked the psychological schemas college students rely on to form their motivational approach to learning opportunities (see Ambrose et al., 2010; Bain, 2011). Understanding this need, the present study sought to provide unique insight into the intrapersonal motivation of today's college students in their pursuit of academic achievement. To provide such insight, the study explored the causal effects of student mindsets – or the implicit beliefs about the nature of intelligence – on the academic motivation and achievement of first- and second-year college students enrolled in science, technology, engineering, or math (STEM) courses. Investigation of these causal connections was accomplished through the development and implementation of a three-stage study.

The first stage of this study sought to validate Dweck's (1999) motivational model of achievement at the post-secondary level through the use of multivariate modeling statistical analyses. Data were collected from a sample of first- and second-year students enrolled in introductory STEM courses at a highly-selective, public, research-extensive university in the Mid-Atlantic through employment of scales developed by Dweck and her colleagues (Dweck, Chiu & Hong, 1995; Dweck & Leggett, 1988; Dweck & Sorich, 1999; Midgley et al., 1998). These scales measured student self-beliefs and motivational variables that, according to Dweck's (1999) conceptual model, influence student achievement. Structural equation modeling (SEM) was then used to test the hypothesized validity of Dweck's model according to the sampled population.

In the second stage of the study, the author sought to increase the absolute fit of the model by introducing an academic self-perception factor to Dweck's (1999) original model. Data measuring students' academic self-perceptions were collected utilizing the

Self Description Questionnaire III (SDQ III) (Marsh & O'Neill, 1984) and the *Problem Solving Self-efficacy Scale* (Bandura, 2006). Data from these scales combined to form a higher-order latent factor that was then theoretically appended to the original model to form a new hypothesized model of academic motivation. The specified stage-two model was also tested through SEM analysis to determine if accounting for a student's academic self-perception increases the predictive power of Dweck's (1999) conceptual model. The final stage of the study considered the results presented from the first- and second-stage models and, in accordance with the theoretical and empirical evidence provided by the models, proposed modifications to best explain the influence of mindsets on motivation and achievement at the post-secondary level.

The attempt to validate Dweck's (1999) motivational model of achievement among college students provides a number of theoretical and practical benefits to the scholarship of teaching and learning. Theoretically, a viable model of motivation and achievement motivation furthers the understanding of how self-beliefs influence intrapersonal motivation and academic achievement at the college level. Practically, a greater understanding of these relationships has the potential to positively influence the way practitioners organize their pedagogy to promote higher levels of student motivation.

Stage-one and Stage-two Hypothesized Models

As noted above, Dweck's causal model hypothesizing a relationship between students' mindsets (or implicit theories of intelligence) and academic achievement has been tested successfully at the K-12 level (Blackwell et al., 2007). According to data collected from sixth- and seventh-grade students, the model suggests that junior high school students' implicit theories of intelligence directly affect their goal orientation and beliefs about effort (see Figure 2). The model also suggests that implicit theories of intelligence indirectly influence achievement outcomes through the mediating relationships between goal orientation, effort beliefs, failure attribution, and students' chosen academic strategies. While Blackwell and her colleagues (2007) were able to achieve a tenable explanation of the relationships between these factors at the K-12 level, no study had tested this conceptual model at the post-secondary level prior to the present study. However, many of the proposed relationships within the model had been observed in real-world college environments or tested in laboratory settings among college students (e.g., Grant & Dweck, 2003; Hong et al., 1999; Robins & Pals, 2002). Having demonstrated a tenable model at the K-12 level and observing significant relationships among the hypothesized factors at the college level, it was feasible to directly test the same conceptual model among a sample of students enrolled in classes at the post-secondary level.

It is important to note that, while the efficacy of this model has been demonstrated at the K-12 level (Blackwell et al., 2007), there is a certain segment of the motivation literature that calls into question the conceptual relationship between mindsets, goal orientation, and academic strategies at the post-secondary level. Several scholars (e.g., Braten & Strømsø, 2004; Dupeyrat & Marine, 2001) have argued that the mediating effects of goal orientation on the relationship between mindsets and academic achievement may be spurious. In a study of young adults returning to college, Dupeyrat and Marine (2005) found that a growth mindset does not fully coincide with mastery goal orientation; simultaneously, performance goal orientations lead to both mastery-oriented academic strategies and helpless response patterns. In light of the many discrepant findings concerning goal-orientation in the model, the first stage of this study sought to validate Dweck's (1999) model at the collegiate level by specifying the model as originally hypothesized. A stage-two modified hypothesis model (see Figure 3) then considered whether academic self-perception might elucidate the role of goal orientation in the model. This model was conceptualized according to findings by Dweck and Leggett (1988) that has suggested students' academic self-perceptions work with their growth or fixed mindset to influence goal orientation (in addition to other motivational factors).It was hypothesized in the second-stage model that the appended factor would account for the discrepancy between Dweck's conceptual model and inconsistencies in the literature.

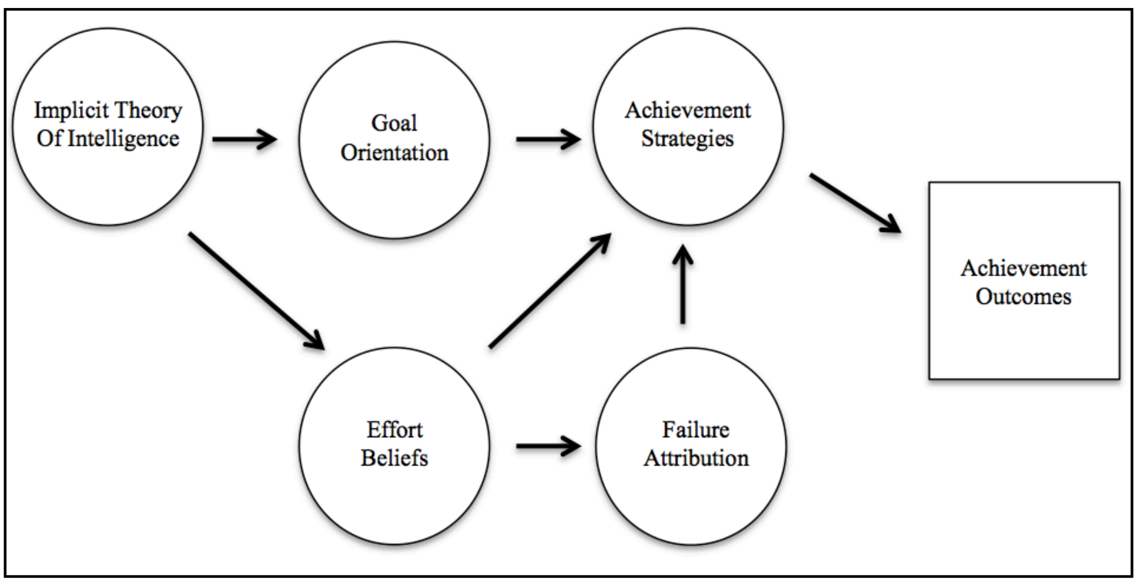

Figure 2. Dweck's (1999) structural model of motivation and achievement demonstrating significant processes linking implicit theories of intelligence and other motivational constructs to academic achievement outcomes. Adapted from "Implicit Theories of Intelligence Predict Achievement Across Transition: A Longitudinal Study and an Intervention," by L. S. Blackwell, K. H. Trzesniewski, & C. S. Dweck, 2007, *Child Development, 78*(1), p. 253. Copyright 2007 by Society for Research in Child Development, Inc. Referred to throughout this study as the *stage-one model*.

To justify modifications to Dweck's (1999) model, this study used Weiner's (1986) attribution theory of motivation to scaffold the assessment of the proposed factor relationships. As noted previously, attribution theory suggests that academic motivation stems from students' predictions of what is possible based on evaluations of what has previously occurred. Weiner's theory also suggests that individuals utilize a set of psychological schemas, or causal antecedents, to frame the evaluations of prior experience (detailed in chapter two). In Dweck's (1999) conceptual model, mindsets act as one of these causal antecedents by framing how students think about their past achievement. If students have experienced failure in the past, the causal attribution they give to this failure is partially dependent on whether they believe their intelligence is malleable or fixed. If fixed, students may attribute the failure to low ability. If malleable, students may attribute the failure to other causes (e.g., lack of applied effort). Therefore, if mindsets are serving as a causal antecedent in Dweck's model, and this causal antecedent does not provide an adequate explanation of the role goal orientation plays in the model, it is likely there is another causal antecedent that may modify this relationship.

In an examination of goal orientation at the collegiate level, Grant and Dweck (2003) found that prior academic achievement shaped the way goals affect achievement outcomes. This is consistent with Weiner's (1986) belief that past experiences play a role in future outcomes. Other research (see Bandura, 1995; Marsh, 1990) has also suggested that academic self-concepts and self-efficacy, or the academic self-perceptions a student has about his or her academic ability and competence, play an active role in motivation (specifically goal formation) and academic achievement. Since Weiner's attribution theory suggests that students refer to their past academic experiences as a catalyst of motivation, and in light of Grant and Dweck's (2003) findings, it was plausible to hypothesize that a student's academic self-perceptions serve as a complimentary causal antecedent that simultaneously affects goal orientation and leads to academic achievement.

Figure 3 represents the alternative hypothesis model for this study that modifies Dweck's (1999) model by including the appended academic self-perception factor. The underlying hypothesis of the model suggests that, in addition to Dweck's original model of motivation, domain-specific measures of perceived self-concept and self-efficacy in the students' enrolled courses (i.e., science, technology, engineering, math) would account for the spurious relationship of goal orientation described in the literature. While students differentiate themselves between entity and incremental theories of intelligence (i.e., fixed vs. growth mindsets), they simultaneously attune to their academic self-perceptions to make causal decisions in their goal orientation. Inclusion of an academic self-perception factor in the model also added an additional explanatory factor in the implied causal relationship of motivation and achievement represented by the direct effects of perceived self-concept and self-efficacy on academic strategies and academic achievement (Marsh, Trautwein, Ludtke, Koller, & Baumert, 2005).

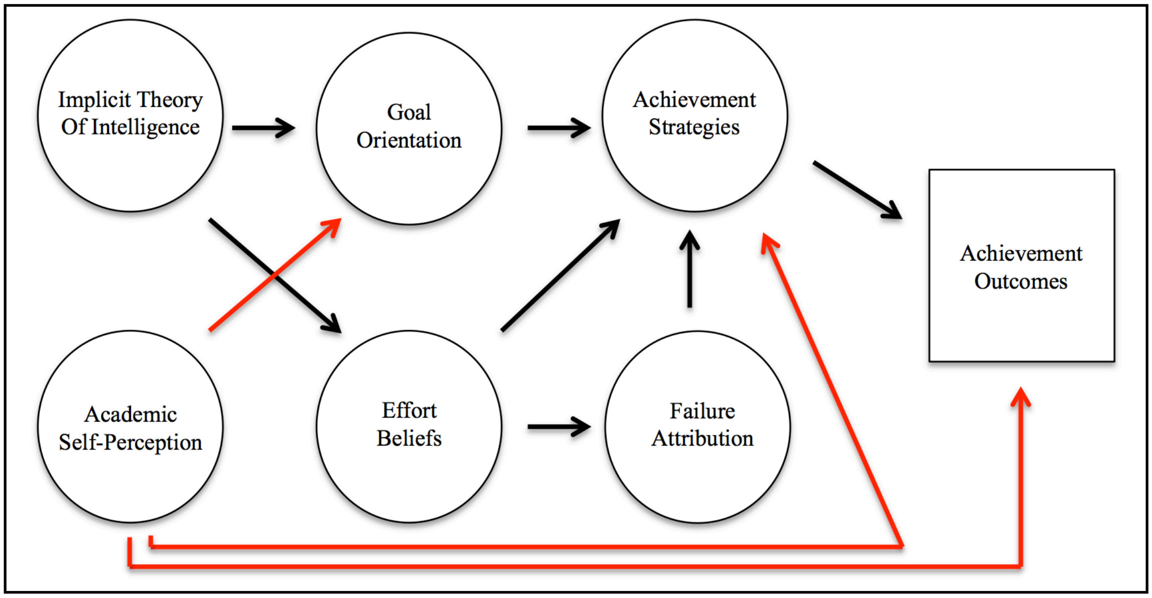

Figure 3. Alternative hypothesis model of motivation and achievement. The model was adapted from Dweck's (1999) motivational model of achievement, introducing a measure of academic self-perception. Theory suggests that the introduction of academic self-perception may account for the spurious effect of goal orientation encountered in the literature. Note: items in red represent additions to Dweck's original specifications.

Research Questions

To further understand the intrapersonal motivational framework of college students, this study explored the effects of student mindsets (i.e., students' implicit theories of intelligence) on academic achievement at the post-secondary level through validation of Dweck's (1999) motivational model of achievement and testing of a secondary hypothesized model. First- and second-year students at a highly selective, public, research-extensive university in the Mid-Atlantic enrolled in predetermined introductory STEM courses were randomly sampled and asked to complete a self-administered survey developed by multiple scholars in the field of motivation, self-perception, and achievement to measure variables related to mindsets and achievement motivation. Demographic variables and measures of academic achievement were collected via the institution's office of institutional assessment to inform the analysis. Multivariate modeling was then employed to highlight the implied causal links between the latent factors that provide a framework of motivation and achievement at the post-secondary level.

This study sought to answer the following research questions:

(a) Do mindsets (i.e. students' implicit theories of intelligence) play a significant role in the motivation and academic achievement of first- and second-year students enrolled in STEM courses at the collegiate level;

(b) If so, do these relationships conform to the specified parameters proposed by Dweck's (1999) motivational model of achievement; and

(c) Does the addition of an academic self-perception factor (a higher-order factor encompassing domain-specific measures of self-concept and self-efficacy) add to the explanatory power of Dweck's theory, using a sample of first- and second-year college students enrolled in STEM courses?

Based on the proposed conceptual model, this study posed three hypotheses regarding the role of mindsets as psychological determinants that create motivational frameworks for achievement motivation:

Ho_1 = Mindsets will play a significant role in the motivation and academic achievement of first- and second-year students enrolled in STEM courses at the collegiate level.

Ho_2 = However, Dweck's (1999) specifications will exhibit ill-defined fit among post-secondary students given the limitations expressed in prior research that suggests goal orientation is a poor mediator of the relationship between student mindsets and achievement strategies (e.g., Dupeyrat & Marine, 2005).

Ho_3 = The introduction of an academic self-perception construct will add to the causal explanation of motivation and achievement while increasing the absolute model fit of Dweck's (1999) motivational model of achievement. When introduced to the proposed model, academic self-perception will account for the discrepant relationship between mindset and goal formation.

Definition of Terms

The initial models assessed by this study were considered *nested* models: that is, each of the relationships specified in Dweck's (1999) motivational model of achievement (see Figure 2) were replicated in the alternative hypothesis model (see Figure 3). The primary constructs that comprised the nested models include (a) implicit theories of intelligence (or mindset), (b) goal orientation, (c) effort beliefs, (d) failure attribution, (e) academic effort strategies, (f) academic self-perceptions, and (e) academic achievement. The following section provides definitions and briefly describes the data collection method utilized for each construct.

Implicit Theories of Intelligence (or Mindset)

A student's mindset is his or her implicit belief in the malleability of intelligence. Students with a growth mindset (i.e., incremental theory of intelligence) believe intelligence can be altered through effort, while students with a fixed mindset (i.e., entity theory of intelligence) view intelligence as innate and unchangeable. Mindsets serve as psychological schemas that frame how students approach achievement opportunities. To determine whether the college students who participated in the study held a growth or fixed mindset, the proposed research used the *Implicit Theories of Intelligence* scale developed by Dweck and her colleagues (1995).

Goal orientation

A student's goal orientation refers to the propensity of a student to craft learning goals or performance goals when presented with achievement opportunities. Learning goals help students focus on increasing ability, while performance goals are used to display ability. Subscales from Midgley et al.'s (1998) *Patterns of Adaptive Learning Survey* (PALS) was used to determine the extent to which college student who participated in the study were oriented towards learning or performance goals.

Effort Beliefs

While children do not distinguish between effort and ability until around the age of twelve (Nichols, 1984), bifurcation of these concepts leads students to divergent beliefs about the utility of effort. Some students believe applied effort can lead to positive outcomes. Others conceptualize ability as a static trait, and therefore believe effort is only a sign of weakness (or lack of ability). To determine the degree to which the respondents in this study believed in the utility or futility of effort, this study used a subscale of Dweck and Sorich's (1999) *Effort Orientation Inventory* (EOI).

Failure Attribution

When faced with failure or situations where failure is imminent, students tend to attribute unsuccessful outcomes to either a lack of effort or a lack of ability (Dweck & Sorich, 1999). Failure attributed to a lack of effort indicates that students believe the outcome's locus of control was internal. Students who attribute failure to a lack of ability believe the outcome was caused by circumstances outside their control. In the present study, failure attribution was also measured according to a subscale of the EOI.

Academic Strategies

Academic strategies composed the third and final subscale of the EOI. This subscale measured the propensity of a college student to choose positive, mastery-oriented strategies or negative, helpless response patterns in light of challenging achievement opportunities. Mastery-oriented strategies may include increased studying, raising questions, or harder work. Helpless response patterns might include procrastination, cheating, or dropout.

Academic Self-Perception

Academic self-perception denotes how a student views his or her general academic ability along a continuum from low to high. Students typically refer to prior achievement outcomes when forming their current self-perceptions (Marsh and Craven, 2006; Bandura, 2001). For this study, the academic self-perception factor served as a higher-order factor that included two sub-constructs: students' perceived self-concept and self-efficacy in domain-specific categories of science, technology, engineering, and math. While students may have a general view of their academic competence, domain specific refers to an individual's academic self-perceptions in specific subject areas. The participants' domain-specific self-concept was measured through a subscale developed for Marsh and O'Neill's (1984) *Self Description Questionnaire III*, and the participants' domain-specific self-efficacy was measured by the *Problem Solving Self-efficacy Scale* (Bandura, 2006).

Academic Achievement (Outcome Measure)

This study followed the recommendations of Elliot & Dweck (2005) who suggested that *achievement* be couched in terms of *competence*, where competence "may be defined as a condition or quality of effectiveness, ability, sufficiency, or success" (p. 5). Academic achievement was therefore defined as the student's success in an academic domain. For this study, end-of-course grades assigned by professors represented the academic achievement outcome measure.

Significance of the Study

While any number of benefits are accrued from attending an institution of higher education (see Pascarella & Terenzini, 2005), there is a general consensus that learning should be the foremost outcome; and yet, contemporary SOTL research suggests that the instruction-centered paradigm so prevalent in today's classrooms does not provide sound footing for advanced learning outcomes (Fink, 2013; Tagg, 2003). Scholars and instructors alike are instead ushering in a new paradigm of teaching that casts the student as the most important piece of the learning equation. Consequentially, this movement requires that scholars explore the vast connections between teaching and learning outcomes. SOTL efforts to understand these relationships have almost exclusively focused on the effects of classroom environments on student achievement (e.g., instructor pedagogy, access to information technology, exposure to diversity). There is, however, a simultaneous need to understand how the student psyche influences motivation and achievement apart from classroom effects. To provide such insight, this study explored the links between mindsets and achievement motivation at the post-secondary level. The addition of this heretofore missing piece of the learning outcome equation furthers SOTL efforts by offering empirical links between students' internal psychological processes with achievement outcomes. It also serves to improve instructional practice; by exposing faculty to the way mindsets effect student motivation in the classroom, instructors can fine-tune their pedagogy to provide optimal learning environments for their students.

CHAPTER 2

LITERATURE REVIEW

This study provided insight to better understand the intrapersonal motivation of first- and second-year college students by assessing the implied causal effects of students' implicit theories of intelligence (or *mindsets*) on their academic achievement. This chapter begins with a brief description of the role motivation plays in academic achievement. The chapter then provides a description of the theoretical framework that guides the assumptions of the proposed study: Weiner's (1986) *attribution theory* and the specific roles of causal antecedents such as mindsets and academic self-perceptions in the development of intrapersonal motivation. The chapter then details the development and research behind Dweck's (1999) motivational model of achievement. In particular, attention is paid to the ways that attribution theory rationalizes each of the five latent motivational constructs in Dweck's theory (i.e., mindsets, achievement goal orientation, effort beliefs, failure attribution, and academic effort strategies). Finally, the chapter concludes with a review of the literature and supporting research concerning the effects of academic self-perception as a second causal antecedent in intrapersonal motivation, which suggests the use of the measure can enhance the causal analysis of mindsets on achievement outcomes. The section also reviews the best-practice techniques for measuring academic self-perceptions to inform intrapersonal motivation.

The Role of Motivation in Academic Achievement

Motivation is a multifaceted construct, and multiple compendiums have been published in an attempt to detail the various aspects of the construct as it relates to academic achievement (see Elliot & Dweck, 2005; Wentzel & Wigfield, 2009). The term motivation is derived from the Latin verb *moveo*, or “to move.” Thus, motivation seeks to describe the ways or reasons an individual acts in a given circumstance. The achievement motivation construct in particular seeks to understand the intent behind the behaviors that lead to achievement. According to achievement theory, motivation (or motives) plays three central roles in achievement: motives select, orient, and energize behavior (McClelland, 1987).

In a review of the literature concerning individual motive dispositions, Schultheiss and Brunstein (2005) sought to describe why individuals desire to achieve competence. In specific circumstances or regarding particular behaviors, individual motivation may not be readily apparent. Schultheiss and Brunstein argued that this ambiguity would lead researchers (e.g., McClelland, 1987) to a novel concept: motivation might be subdivided into an implicit motive construct and an explicit motive construct. Implicit motives depend on affective preferences where behavior is determined by the potential for individual reward or pleasure (McClelland, 1987). Explicit motives, on the other hand, are contingent on the normative expectations for a group (e.g., family, peers, society) and orient] behavior toward what the group believes is desirable (McClelland et al., 1989). Thus, achievement behavior may be driven by either internal incentive derived from the pleasure of the activity itself or through social incentive.

In a now famous exposition on the differences in explicit and implicit motives, McClelland, Koestner, and Weinberger (1989) contended that achievement motivation is cued either consciously (through identifiable stimuli) or unconsciously (through spontaneous reaction to unidentifiable stimuli). In either form, achievement motivation employs the use of psychological schemas in the decision to attend to conscious or unconscious cues. These schemas act as cognitive generalizations, derived from past experience, that organize and guide the processing of information in decision-making (Markus, 1977; Piaget, 1962). In other words, motives are established through psychosocial processes that evaluate what has happened in the past, what incentives are available in the present, and what the outcomes of directed behavior could be in the future. Several schemas that underlie the achievement motivation construct include academic self-perceptions, goal orientation, and effort attribution.

Academic Self-Perceptions

Motivation is partially derived from the reflection on one's past experiences and present ability. Therefore, the degree to which a student is motivated academically may be assumed to derive from either direct observation and assessment of past academic behavior (e.g., "I get straight As in math, therefore I must be motivated to achieve mathematically") or by others' evaluations of the individual's perception of past academic performance (e.g., "You're not as good at math as you think you are") (Shultheiss & Brunstein, 2005). These academic self-perceptions serve as schemas – or ways of understanding the world – whereby they inform judgments according to the outcome expectancies that in turn affect motivation.

A student's academic self-perception serves to help predict what the future academic outcome will be of any given behavior (Bandura, 1977). This prediction (i.e., outcome expectancy) motivates behavior for academically confident and academically uncertain students at a different valence. Academically confident students anticipate successful outcomes from academic behavior. These individuals expect to receive good grades on assignments because of either their past performance or belief in their ability to perform at a high level academically. These predictions of positive outcomes help motivate students to achieve academically because of the positive valence associated with academic achievement. Students who are not confident about their academic prospects are motivated in a different direction. These students expect to receive poor grades in achievement opportunities due to their past failures or belief in their low academic ability. These predictions manifest themselves in lower motivation when presented with achievement opportunities (Bandura, 1997).

Achievement Goal Orientation

As stated previously, motivation is dependent on the prediction of outcomes relative to chosen behavior. These predictions serve to select, orient, and energize behavior according to valence. Students are either confident and motivated towards positive expectant outcomes (*approach motivation*) or uncertain and motivated away from negative expectant outcomes (*avoidance motivation*) (Elliot, 2005). In either paradigm, the student ascribes to a selected achievement goal orientation.

Dweck and Leggett (1988) identified two achievement goal orientations in studies performed with adolescents in junior-high and high school. Their research suggested an individual's achievement goal represented the purpose for which a student engaged in achievement-oriented behavior. Students whose behaviors sought to demonstrate their competence chose *performance goals*. Students whose behaviors sought to develop competence and task mastery, in contrast, chose *learning goals*. Both performance goals and learning goals represent approach motivation, whereby the student moves toward expectant outcomes (e.g., success or failure). A third achievement goal, *performance-avoidance goals*, was also identified in research by Elliot and his colleagues (1999; Elliot & Church, 1997; Elliot & Harackiewicz, 1996). Undergraduate students who sought to avoid a demonstration of competence choose performance-avoidance goals. This is presumably due to low perceived self-competence and can lead to avoidance motivation (Elliot et al., 1999). These three goal orientations serve as schemas and central determinants of motivation patters that frame the purposes of achievement (Elliot, 2005).

Effort Attribution

Motivational theorists (e.g., McClelland, 1987; Nichols, 1984) have long believed that effort played an integral role in academic motivation. Scholars were particularly interested in the role that increased effort played in academic achievement, specifically in light of high expectations (Wigfield & Eccles, 2000) or through the process of self-regulation (Zimmerman, 1990; Zimmerman & Cleary, 2009). The more a student is motivated to succeed, the more likely the student will employ effort in a given achievement task. Yet this relationship between increased motivation and increased effort can be considered reciprocal in nature. The ways in which students think about effort and attribute success or failure to the amount of effort expended can prompt changes in motivation (Jones & Berglas, 1978).

Dweck and Leggett (1988) uncovered two types of beliefs about effort. In their research, they found that some students attribute academic success to effort and hard work. Other students believe that the expenditure of effort is a sign of low intelligence. In achievement situations, these students attribute their successes and failures to their ability level rather than effort expended. These students have been shown to exhibit less motivation with regard to achievement strategies such as studying or exhibiting on-task behavior in the classroom (Rhodewalt, 1994; Midgley, Arunkumar, & Urdan, 1996).

Theoretical Framework: Weiner's (1986) Attribution Theory

There is no one definition or understanding of motivation; understandably, this has led to multiple theories and considerable disagreement as to the nature of motivation (Wentzel & Wigfield, 2009). Pintrich (2003) offers a reasonable description by suggesting motivation is "what gets people going, keeps them going, and helps them finish tasks" (p. 104). Motivation theories regarding academic achievement typically refer to those processes that help determine and regulate activities and behavior that reference academic goals (McClelland, 1987). While a number of motivational theories have been used to frame the relationship between motivation and academic achievement, such as achievement goal theory (Maehr & Zusho, 2009; Urdan & Maehr, 1995), self-determination theory (Deci & Ryan, 1991; 2000), and expectancy-value theory (Eccles, 2005; Pekrun, 2000; Wigfield & Eccles, 2000), Weiner's (1986) attribution theory of motivation has been a favorite of social cognitive psychologists for its incorporation of attributional antecedents into the affective, cognitive, and behavioral outcomes of motivation in the school setting (Graham & Williams, 2009).

Attribution theory is a social cognitive approach to human motivation that seeks to describe why people choose behaviors to attain competence (see Weiner, 2005). Originally posited by Heider (1958), attribution theory suggests that people seek reasons for prior success or failure and attribute these outcomes to any number of causes. These attributions then elicit behavioral reactions (i.e., motivated behavior). Many of the contemporary studies using attribution theory to guide their research rely on the attribution theories developed by Weiner (1986). Weiner has proposed two orthogonal frameworks regarding attribution theory: both the *intrapersonal* theory of motivation and the *interpersonal* theory of motivation. Each is described below, with more detail given to Weiner's intrapersonal theory of motivation, which served as the theoretical framework for this study.

Intrapersonal and Interpersonal Motivation

Weiner's (1986) theories of attribution motivation suggest that all motivation is derived from the affective (or emotional) reaction to past experiences. Both Weiner's intrapersonal and interpersonal frameworks rely on the belief that people reflect on their past situations to form predictions about what will happen in the present or future, and that these predictions elicit behavioral reaction. Weiner proposed these frameworks after observing the reactions of young adults (both in and out of college) during particular events. He noticed that after each experience, people demonstrated either a positive or negative emotion: if the event was good, the person felt happy; if the event was bad, the person exhibited sadness. Over time, Weiner and his colleagues observed that even after details of experiences were forgotten, individuals were still able to report the emotions felt as a result of the experience (Weiner, Russell, & Lerman, 1978, 1979). They also noticed that the emotions elicited by the experience formed the basis for the causal ascription each individual made for the experience. Individuals who felt happy after an experience were more likely to attribute the cause of the experience to effort or ability rather than luck. These individuals also believed they would feel happy again in similar situations given the previous outcome was perceived to be under their control. In contrast, individuals who experienced negative outcomes felt sad and frustrated and more often reported that the outcome was outside of their control. When asked how they would feel if similar experiences presented themselves in the future, the respondents believed they would likely feel the same way.

The act of internally attributing a cause to a previous outcome, and subjectively predicting future outcomes as a result of this past attribution represents Weiner's (1986) theory of the *intrapersonal* framework of motivation. Intrapersonal motivation can be understood as an individual's self-directed thoughts, feelings, and beliefs used to approach achievement opportunities through four steps. First, an individual internally reflects on past achievement outcomes and those emotions evoked from said outcomes. Second, the individual attributes these emotions to the cause of the achievement outcomes (e.g., ability, effort, luck). Identifying these causal attributions, the individual then predicts what might happen in similar achievement opportunities in the future. Finally, if the individual experienced positive emotions as a result of prior outcomes and believes these can be experienced again, he or she will seek to reproduce outcomes that evoke this positive affect. If the individual experienced negative emotions as a result of prior outcomes, he or she will seek to minimize those outcomes that evoke similar negative affect.

For example, a student's intrapersonal motivation towards a future math exam is partially based on how he or she felt as a result of past successes or failures. A student who has recently failed a math exam may feel sad as a result of failure. The student will seek to understand what caused the failure, try to predict what would happen and how he or she would feel at the next math exam as a result of the causal attribution of his or her past failure, and seek to engage or avoid behaviors that would reproduce the sadness originally felt.

Weiner (1986) was also aware that people experience events as part of a social construct. As a result of experiences, significant others (e.g., teachers, parents, and peers) also make causal attributions to an individual's experiences. In the example of the student who has failed a math exam, the instructor of the math course may feel disappointed and attribute the failure to a lack of effort. The instructor's emotions may then elicit behavior from the student. The external relationship between the attributions, emotions, and behaviors elicited by others and the behavioral reaction of the individual to these social pressures represents Weiner's *interpersonal* framework of motivation. Similar to intrapersonal motivation, interpersonal motivation is reliant on the emotions induced by an event.

While ecological forces in academic environments require students to process their motivation through the interpersonal framework, they too must attend to their intrapersonal motivation. Weiner (2005, 2006) recognized this and suggested that interpersonal and intrapersonal frameworks are orthogonal constructs, allowing researchers to bifurcate these frameworks and study one or the other independently. This study was particularly interested in the internal motivation of students as they approach achievement opportunities in college; therefore, the study's theoretical framework is based on Weiner's (1986) model of intrapersonal motivation.

Figure 4 offers a visual interpretation of Weiner's (1986) intrapersonal attribution theory of motivation. As noted previously, Weiner's theory suggests the process of developing intrapersonal motivation begins by reflecting on prior outcomes and the dependent affect resulting from those outcomes. As people reflect on prior outcomes and the feelings they produce, cognitive schemas (e.g., perceived self-competence, causal rules, hedonic biases) develop to assist the search for causal meaning in events. The cognitive and affective reflections over the outcomes of a previous event serve to ascribe reasons – or causal attributions – to the outcome and the outcome's dependent affect. Wiener's theory suggests people then assess these causal attributions according to a triarchic model of causal ascription, where causality is subject to (a) locus, (b) stability, and (c) controllability. Finally, the interaction between these three causal dimensions promotes the motivational consequences that determine behavior. The following sections of this review seek to better explain how causal antecedents, causal analysis, and the psychological determinants of motivated behavior play a role in determining intrapersonal motivation.

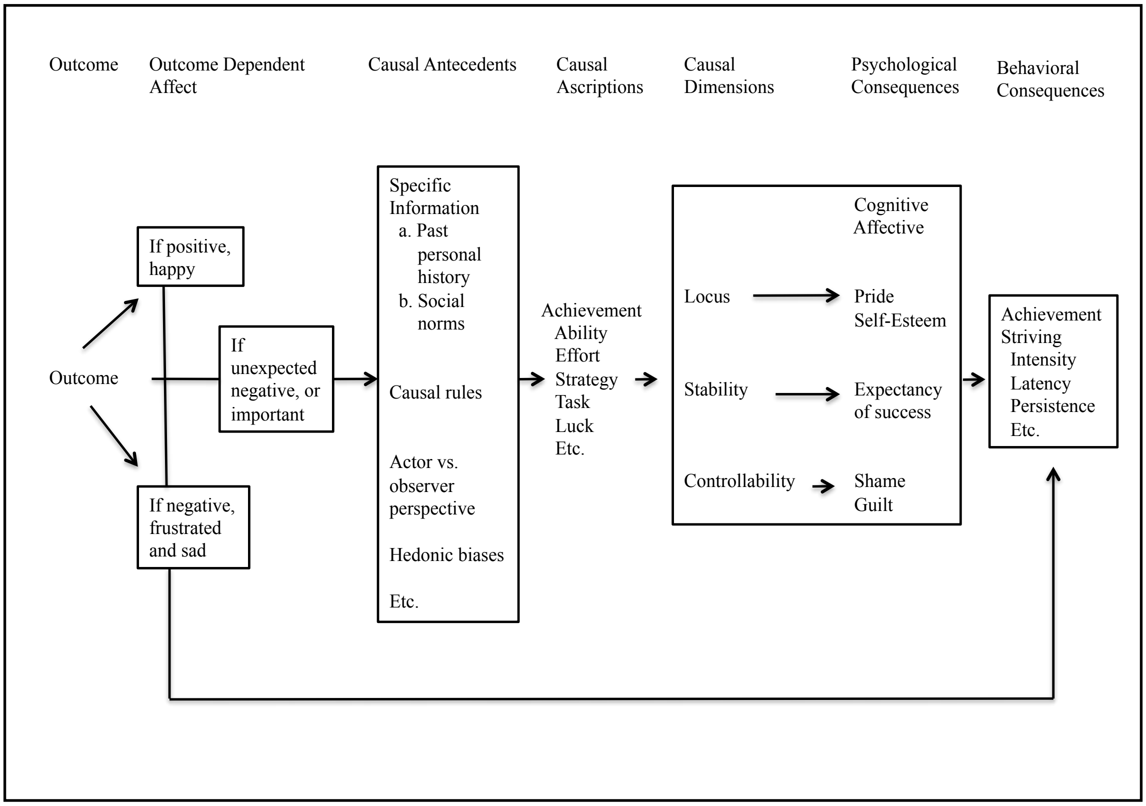

Figure 4. Wiener's (1986) intrapersonal attribution theory of motivation. Adapted from "Motivation from an Attribution Perspective and the Social Psychology of Perceived Competence" by B. Weiner, 2005, in A. J. Elliot and C. S. Dweck (Eds.), *Handbook of Competence and Motivation*, New York, Guilford Press. Copyright 2007 by The Guilford Press.

Causal Antecedents

When people search for reasons why something happened, they use a variety of cues to guide their inferences. According to Weiner (1986, 2005), the first cue is often the immediate emotions felt as a result of the outcome. Soon after, people begin to think about similar past experiences and the causal attributions made for those outcomes. Overtime, recurrent attributions form cues that ease this reflective process. Weiner refers to these cues as *causal antecedents*. Causal antecedents are cognitive frameworks – or schemata – that have been derived from past experiences to help define the limits of causality. In other words, causal antecedents provide rules for what could and could not have caused an outcome. Weiner (1986) noted that prior attribution theorists (i.e., Jones & Davis, 1965; Kelly & Michela, 1980) had demonstrated that people seek to derive explanations for events by thinking about what has happened in the past. Causal schemata are developed as a result of these observations and stabilize over time to help ease the process of casual attribution.

To offer a metaphor for causal antecedents, picture an instruction manual. An instruction manual seeks to describe the processes of how things work. The instruction manual may also define what is possible and what is not possible. In essence, an instruction manual serves to link cause and effect. Causal antecedents act like an instruction manual, defining what causes might be possible, what causes are probably not possible, and how the individual should interpret an outcome as a result of what has happened in the past. Kun and Weiner (1973) observed the effects of causal antecedents in their study of the causal attribution of academic success. They asked 197 undergraduates to envision success in both an easy task and a difficult task. The students were then told that the people who succeed in each task had a high level of ability and were then asked to infer the presence of effort in both the easy and difficult tasks. Accordingly, the participants in the study suggested that little effort was needed in the easy task, while a considerable amount of effort was needed in the difficult task. Kun and Weiner surmised that the participants in the study were referring to causal antecedents to infer that success in the face of increased difficulty requires something more than ability alone. These antecedents, or causal schemata, helped the students attribute the reason for success on a difficult task as effort.

The models of motivation and achievement explored in this study suggest that a student's mindset and academic self-perceptions act as causal antecedents: that is, they are used as referents in the cognitive processing of causal attributions in one's intrapersonal motivation. Mindsets act as a framework or rules that help define intelligence as either fixed or malleable. Students may use this schema to attribute their success or failure to a particular cause (e.g., ability, effort, luck). Academic self-perceptions can also serve as a benchmark for determining causality. Students may ascribe causation to an outcome based on whether past experience has led them to believe they are competent or incompetent at a given task. The degree to which mindsets and academic self-perceptions serve as causal antecedents is described in more detail later in this chapter.

Causal Analysis

In an overview of the contemporary influences of attribution theory, Graham and Williams (2009) suggested that achievement could be attributed to one or more of six causal factors: ability, effort, task difficulty, luck, mood, and help or hindrance from others. According to Weiner (2005), ability and effort are the most salient causal attributions in today's western culture. However, whether people attribute achievement to ability, effort, or any other factor is determined through the systematic analyses of prior experience and causal antecedents. According to Weiner's (1986) intrapersonal theory of attribution motivation, people seek to determine causality through a triarchic assessment of locus, stability, and controllability.

Locus. Causation must have an origin. Outcomes are either caused by internal factors, or they are caused by environmental factors. Internal causes originate within the individual and are separate from the environment, such as ability or effort. External causes are those forces that affect outcomes, irrespective of the individual. Weiner (1986) credits the theory of locus orientation to the work of Heider (1958), who proposed an analogy of rowing a boat across a lake on a windy day to represent the locus of causality. Heider suggested that the success of rowing across the lake can be attributed to internal factors (i.e., rowing technique, strength, navigation) or to environmental factors (e.g., wind, currents). Likewise, academic achievement can also be caused by internal factors (e.g., ability, effort) or environmental factors (i.e., task difficulty, proper or improper instruction, chance).

A contemporary of Weiner, de Charms (1968) suggested that there is a great deal of motivational power associated with the ways in which people perceive causal attributions as internally or externally located. de Charms theorized that people who internally locate causation view themselves as, to use his terms, *the Origin* of what is to come; that is, a sense of causal efficacy is made available to those who internally locate causation. In contrast, those who tend to locate causation externally understand themselves as *the Pawn* of those forces beyond their control: the possibility to affect outcomes is not present. Weiner (1986) expounded on this idea by suggesting that an internal locus orientation may convince people that they have the requisite ability to succeed. An external locus orientation, however, may negatively influence people’s sense of ability to achieve outcomes: success, according to the external locus orientation, depends on the conditions of individual environments.

Stability. In an attempt to describe how locus influences causal attributions, Weiner and his colleagues (1971) observed a new phenomenon regarding the internal and external causes of behavior. They determined that some causes – both internal and eternal – remain constant while others fluctuate. Weiner (1986) theorized that the volatility of a cause has the potential to affect how an individual attributes causality to an outcome. In the achievement domain, the degree to which someone employs effort to reach an outcome can range from low to high. Yet this range is variable; sometimes a student might employ high effort, and in other situations may withhold effort. Effort, in this sense, can be construed as an unstable cause with an interior locus. Luck, on the other hand, is an unstable cause with an external locus. Sometimes students are lucky. Sometimes they are not. In either situation of luck, the cause is externally located and fluctuates. Highly stable causes may include rigor or biases. The difficulty of a particular class may decrease with time, but rarely does this happen quickly. Similarly, biases may change, but over time.

Controllability. Controllability accounts for the third analytical dimension of causal attribution as proposed by Weiner (1986). Controllability can be defined as one's perception that causal forces can either be willingly produced through behavior (controllable) or not be of one's volition (uncontrollable). Wiener proposed that both internally and externally located causes can be categorized according to controllability (e.g., effort is internal and controllable while bad luck is external and uncontrollable) and stable and unstable causes (biased instruction is stable and uncontrollable, while the failure of friends to help is unstable yet controllable). One's perceived level of control thus shapes the understanding of what causes outcomes and how one is motivated towards future outcomes.

Table 1 was adapted from Weiner's (1986) review of the triarchic systematic analysis of causal attribution (p. 51). In the table Weiner demonstrates the eight possible classifications for perceived causal attributions of achievement failure when factoring in to account locus, stability, and controllability. Weiner stressed that the purpose of classifying causal attributions (e.g., ability, effort, task difficulty, luck, mood, help or hindrance) is to determine how the attribution of these causes map onto the two main psychological determinants of motivated behavior: (a) expectancy and (b) value.

Table 1

Perceived Causes of Achievement Failure as a Result of Systematic Analysis of a Locus x Stability x Controllability Classification Scheme

Dimension Classification			
Locus	Stability	Controllability	Possible Cause of Failure
Internal	Stable	Uncontrollable	Low aptitude
Internal	Stable	Controllable	Never studies
Internal	Unstable	Uncontrollable	Sick the day of exam
Internal	Unstable	Controllable	Did not study for this particular exam
External	Stable	Uncontrollable	Exams are very difficult
External	Stable	Controllable	Instructor is biased
External	Unstable	Uncontrollable	Bad Luck
External	Unstable	Controllable	Friends Fail to Help

Note. Adapted from *An Attributional Theory of Motivation and Emotion* by B. Weiner, 1986; New York, Spring, p. 51. Copyright 2007 by B. Weiner.

Psychological Determinants of Intrapersonal Motivation

The individual's search for causality creates a framework for making predictions about future situations. As noted in the previous sections of this chapter, an individual's causal antecedents and the analysis of causality's locus, stability, and controllability allow the individual to generalize across prior situations to form predictions (Kun & Wiener, 1973; Weiner, 1986l; Weiner et al., 1971). These predictions then influence individual behavior when faced with achievement opportunities. According to Weiner's

(1986) theory of intrapersonal motivation, predictions for future outcomes are composed of two qualitatively different estimates that serve as the determinants of behavior: the future event's likelihood of success (i.e., expectancy), and the future event's likelihood of providing incentives (i.e., value).

Expectancy. Of the three causal dimensions, stability is understood to have the strongest effect in determining the likelihood – or expectancy – of success or failure (Weiner, 1986). In a review of nearly fifteen studies conducted on the stability of causal attributions and predicted achievement, Weiner (1992) noted that when causation of prior events is considered stable, the same or similar outcomes are expected in future events of the same nature. The opposite was observed to be true of unstable causal attributions: when prior causes seemed unstable, the prediction of future outcome seemed similarly arbitrary. In the prior example of the student who fails the math test, attribution theory suggests that the student who ascribes failure to a lack of ability (a stable cause) is most likely to expect he/she will fail on a future math test. A different student who attributes failure to bad luck or lack of preparation (an unstable cause) will be less likely to predict the outcome of a future math test.

Weiner (1986) proposed that levels of expectancy for future outcomes intensify the more an individual attributes a stable cause to an experienced outcome. In relation to this claim, Weiner also suggested that the level of expectancy for future events is unchanged when past events were attributed to unstable forces. Weiner and his colleagues (Weiner, Nierenberg, & Goldstein, 1976) first observed the effects of stable attribution while investigating social learning among undergraduates at the University of California. In this study, participants engaged in a consecutive series of puzzles resulting in either success or failure. After the conclusion of each puzzle, the participants would rate their perceptions of whether they would succeed or fail on a following set of ten puzzles. Participants' attribution was also measured on a scale of stability, where one item asked, "did you succeed on this task because you are always good at these kinds of tasks, or because you tried especially hard on this particular task" (Weiner et al., 1976, p. 61). According to this measure, ability was understood to be a stable cause while effort was an unstable cause. Weiner and his colleagues compared the means of these data. Their results demonstrated that those who attributed a stable cause to the puzzle outcome indicated a higher expectancy on future trials, while those who attributed an unstable cause to the puzzle outcome remained unchanged in their prediction of what was to happen when solving additional puzzles after each successive iteration of the puzzle.

Value. According to Weiner's (1986) theory of intrapersonal motivation, expectancy is a necessary but not sufficient factor for determining motivated behavior. To reinforce this belief, Weiner once quipped, "I can surely beat my 5-year-old neighbor at tennis, yet I infrequently challenge her to a match in spite of my love of winning" (1986, p. 117). Wiener proposed a second, equally important factor must also play a role in motivated behavior: a person's *value* incentive. In essence, people make a determination about the degree to which achievement is of value to them in addition to the likelihood or expectancy of acquiring it.

Weiner's theory suggests that emotions derived from both past experiences and the analysis of locus and controllability on causal attributions shape the value incentive of future outcomes. This is accomplished by predicting the emotions one will feel after completion of a task and comparing this predicted affect to the emotions elicited by prior outcomes. The subjective value of the previously experienced emotions then stimulates a positive or negative reaction to a forthcoming achievement opportunity. The supposition that emotions can lead to behavior, irrespective of cognition, is well documented (see Marien, Custers, Hassin & Aarts, 2012; Vazire & Wilson, 2012; Wilson, 2002). Specifically, Weiner (1986, 2005) suggested that four primary emotions serve to determine subsequent behavior and are linked to the analysis of causal attribution: pride (and in-turn self-esteem), guilt and shame, and helplessness.

Pride. According to Weiner (1982; 1986), feelings of pride are associated with locus orientation. To feel proud or have a sense of high self-esteem, one must ascribe the cause of success internally rather than to the environment. Pride is contingent on believing that the outcome of an event was due to internal forces. A lack of pride, or negative self-esteem, is experienced when the source of failure is also attributed to the self rather than the environment (Stipek, 1983). Harvey and Weary (1981) suggest that when presented with success and failure scenarios, individuals tend to ascribe an internal locus to success and an external locus to failure. This tendency is known as the *Hedonic Bias* and is considered a causal antecedent in Weiner's (1986) attribution framework of intrapersonal motivation. The key to feeling a sense of pride is to locate causation internally.

Guilt and Shame. In contrast to pride, feelings of guilt and shame are associated with controllability (Weiner, 1982; 1986). Both guilt and shame are experienced as a result of not attaining a desired outcome. Though similar, guilt is felt when the cause of the outcome is controllable, while shame is felt as a result of uncontrolled causes. For example, a student who fails an exam because of a lack of effort may experience guilt for having not employed the necessary degree of effort. On the other hand, a student who fails an exam because of a lack of ability may feel shame as ability is uncontrollable. To test these suppositions, Brown and Weiner (1984) asked 493 undergraduates to rate the degree to which 10 emotions were associated with either a lack of ability or a lack of effort. Their results indicated that three emotions – guilt, regret, and remorse – were highly correlated with a lack of effort. The results also indicated that humiliation, disgrace, and embarrassment – all shame-based emotions – were highly correlated with a lack of ability.

Helplessness. Weiner (1986) suggested that learned helplessness is an emotion or feeling that may be formulated over time when multiple outcomes are attributed to a cause or causes that are uncontrollable. Furthermore, Weiner contended that helplessness influences both expectancy of success and the value of the outcome. Failures due to factors of helplessness are linked to low expectations and negative incentives for behavior, while failures that are controllable do not necessitate low expectations or values (Weiner, 1979; 1986). Wiener (1979) and Elliot (1999) demonstrated that feelings of helplessness may result in increased rates of resignation or effort avoidance – both negative responses to achievement opportunities.

Employing Weiner's Intrapersonal Motivation Model as a Theoretical Framework

In order to predict the motivation of individuals in achievement contexts, Weiner (1986) conceptualized a model that incorporates the search for causality with emotional response and affect-contingent behavior. His model demonstrates how the attributions made for success and failure determine how people approach future opportunities for achievement. This process includes reflection, analysis, and prediction. As a causal model, each stage influences the next. Weiner's model has served as an underlying conceptual guide for many contemporary theories of motivation in achievement contexts (e.g., Boyer, 2006; Walton & Cohen, 2007). In particular, Weiner's model of intrapersonal motivation served as a foundation for Dweck's (1999) model of motivation. Dweck (1999) personally noted that Weiner's model as a theoretical framework has contributed to the strength and rigor of motivation analysis. Dweck offered in her summary, "[Wiener's model] allowed researchers to begin to probe systematically into how people's beliefs shaped their motivation" (p. 140). For this study, Weiner's attribution theory was used to expound on the relationships between the variables in Dweck's (1999) motivational model of achievement and justify the inclusion of an academic self-perception factor in this study's stage-two hypothesized alternative model.

Dweck's Motivational Model as an Intrapersonal Model of Motivation

While chapter one laid the groundwork for describing the five constructs in Dweck's (1999) motivational model of achievement, the following sections elaborate on each by reviewing studies that have examined the specific components and their interrelations with achievement. Each section begins with a brief description of the underlying construct in Dweck's model and then addresses the construct's relation to Weiner's (1986) intrapersonal model of motivation. The section then reviews correlational and experimental studies that support the proposed structure of Dweck's model.

Implicit Theories of Intelligence as Causal Antecedents

Dweck first began to craft a theory of student motivation through her research on coping mechanisms in children from kindergarten to the fifth grade. Both Dweck and

Bempechat (1983) noticed that some of these students perceived failure as a learning opportunity and a way to improve their intelligence. Students with this mindset viewed intelligence as malleable, while others viewed intelligence as fixed. This view or *theory of intelligence* serves as a lens through which students believe what is possible (Dweck, 2010). Dweck (1999) has suggested that these self-theories, or mindsets, influence the type of goals students select to pursue as well as the achievement patterns they adopt. Irrespective of whether intelligence is malleable or fixed (see Barsalou, 2010 for a conversation regarding this contemporary debate), there is compelling evidence to suggest that students' beliefs about the nature of knowledge and learning can have a substantial effect on motivation. Dweck's (1999) model contends that students' beliefs about the malleability of intelligence lay the foundation for an entire motivational framework – a theory that has been successfully tested at the K-12 level (Blackwell et al., 2007). The framework suggests a student's mindset influences the achievement goals students seek to achieve, their belief in the role effort plays in achievement, the degree to which they believe they are helpless to overcome failure, and the strategies they utilize to succeed academically. In essence, a student's mindset acts as a causal antecedent or rule that helps the student ascribe meaning to why outcomes occur. According to Dweck (1999), students of an incremental or growth mindset, who believe their intelligence is malleable, have a far greater chance of believing outcomes can be influenced by effort in comparison to those with an entity or fixed mindset – those who believe their intelligence is permanent. In reference to Weiner's (1986) attribution theory, mindsets serve to help students assess the stability and controllability of how intelligence might influence outcomes. Either success is unstable, yet controllable, through the reliance on changes in intelligence, or success is stable, yet uncontrollable, through a dependency on one's fixed amount of intelligence.

Achievement Goal Orientation

The supposition that students adhere to either entity or incremental self-theories of intelligence was originally proposed in concert with research seeking to understand how students utilize goal orientation to motivate learning. In the mid- to late-1970s, researchers (including Dweck) began to postulate that goals serve as central determinants of achievement patterns (Elliot, 2005). To test this hypothesis, Elliot & Dweck (1988) explored the goal orientations of 101 fifth-grade children. Given identical experimental conditions, the researchers found that entity theorists and incremental theorists adopted different goals as a result of the different objectives for each group. Students with fixed mindsets pursued performance goals in order to prove their ability while students with growth mindsets pursued learning goals to scaffold their understanding of new concepts and increase their individual competence.

In order to understand the relationship between these self-theories of intelligence or mindsets and achievement goal orientation, one must understand the theory undergirding achievement goals. According to the seminal work of Nicholls (1978; 1980) on achievement goal formation, young children do not initially distinguish between the concepts of effort and ability: a child believes his or her ability is a result of the direct expenditure of effort. Nicholls' research led him to suggest that it is not until around the age of 12 that students differentiate between the two concepts, adopting a belief that ability or intelligence is a fixed concept.

Nicholls (1984; 1989) went on to postulate that achievement behavior is a direct product of two independent goals: goals where individuals seek to demonstrate their ability (exemplifying a differentiated perspective of effort and ability) or goals where people seek to increase their ability (exemplifying the undifferentiated perspective). Nichols identified these goals as either "ego involvement" whereby individuals are transfixed on the goal of proving one's ability, or "task-involvement" where individuals sought to master the task presented them.

Similarly, Dweck and Leggett (1988) suggested a student's achievement goal represented the purpose for which the student engaged in achievement-oriented behavior. Based on prior research that suggested differentiated goals elicit different types of achievement behavior (Farrell & Dweck, 1985; Nicholls, 1984), Dweck and Leggett (1988) proposed a conceptual model that accounted for the ways that students' mindsets inform achievement goal orientation. In their model, students with fixed mindsets have a need to either demonstrate their intelligence or avoid demonstrating a lack of intelligence. Because intelligence is viewed as an entity that is unchangeable, mastery is understood according to these students as a concept that is proven rather than learned. For students with a fixed mindset, achievement is equated with proven ability, and performance goals are established to either demonstrate how well one performs or hide one's incompetence. Students with fixed mindsets – who according to Dweck and Leggett view achievement scenarios as tests of adequacy – align themselves with performance goals. Contrary to the fixed mindset, Dweck and Leggett postulated that students with a growth mindset care less about demonstrating intelligence and instead focus on learning as the key to academic success. These incremental theorists tended to perceive achievement scenarios as opportunities for growth and employed learning goals to this end.

Both the differences in goal orientation and the ways growth and fixed mindset students approach learning opportunities have been illustrated in several recent studies. In their exploration of students transitioning to junior high school, Blackwell et al. (2007) found the propensity to espouse an incremental theory of intelligence was significantly correlated with adherence to mastery-oriented learning goals (r=.34). These students were more likely to agree with the concept that schoolwork presents an avenue to learn new things rather than assess one's skill as well as more likely to pursue learning goals at the cost of needing to expend effort when compared to entity theorists. Students participating in Hong et al.'s (1999) study at an elite Hong Kong university revealed similar tendencies. Each of the participants in this study demonstrated a lack of proficiency in the English language though success at the school required such proficiency. Hong and her colleagues found that students with a growth mindset were much more willing to participate in a remedial English course than their entity counterparts, controlling for prior ability.

Issues of achievement goal orientation in the literature. While Dweck's (1999) conceptual model suggests that students who hold growth mindsets tend to adopt learning goals and are therefore more likely to adopt successful strategies for achievement, research into the link between these factors has demonstrated several discrepant findings. In a number of studies, the mediating effects of goal orientation on the relationship between student self-theories of intelligence and academic achievement failed to emerge (Dupeyrat & Marine, 2001; Dupeyrat & Marine, 2005; Stipek & Gralinski, 1996).

Spinath and Steinsmeier-Pelster (2001) were able to demonstrate a significant relationship between the self-theories and goal orientation of undergraduates enrolled in a German university, however their findings suggested only a weak correlation between the two factors. At the collegiate level, Robins and Pals (2002) were able to demonstrate a link between mindsets, goal orientation, and self-esteem. However, numerous studies have discredited the causal effect of self-esteem on academic achievement (e.g., Ross & Broh, 2000; Skaalvik & Skaalvik, 2011).

In addition, several studies call in to question the differentiated outcomes of choosing a performance goal versus a learning goal. Five studies by Grant and Dweck (2003) seeking to better understand how goal orientation affects achievement motivation suggested learning and performance goals may not affect achievement and persistence. Over the course of five studies that measured responses from nearly 1000 undergraduate students enrolled at Columbia University, including a longitudinal study of 206 students participating in a difficult pre-med course, the authors found that the impact of students' goal orientations depended on how they were operationalized. The desire to succeed significantly correlated with both learning goals (r=.37) and performance goals (r=.53), and these scores held constant across a two-week timespan (test-retest r=.79). Grant and Dweck found that when challenged, performance goals led to both poorer performance and course departure, while learning goals encouraged sustained motivation and higher achievement. However, controlling for level of challenge, college students with performance goals persisted to the same degree as those with learning goals.

According to Dweck and Leggett (1988), the persistence of students despite their goal orientation may be explained by the influence of academic self-perception. The authors observed that junior-high and high school students with fixed mindsets coupled with high perceptions of their individual academic ability tended to select performance goals and engage in positive academic behaviors that would lead to greater academic outcomes. In contrast, students with fixed mindsets and low academic self-perceptions tended to select performance-avoidant goals, hoping to avoid demonstrating a lack of ability. Those students with growth mindsets, despite disparate perceptions of their self-competence, each selected mastery goals and engaged positive academic behavior. Table 2 depicts these relationships and the moderating effect of academic self-perception on the relationship between theory of intelligence and achievement goal orientation. These relationships add to the postulation that inclusion of an academic self-perception factor may strengthen an analysis of the role mindsets play in motivation and achievement.

Table 2

Relationship Between Implicit Theory of Intelligence, Academic Self-perception, and Achievement Goal Orientation

Theory of Intelligence	Academic Self-Perception	Achievement Goal Orientation
Incremental Theory / Growth Mindset	High or Low	Mastery Goals
Entity Theory / Fixed Mindset	High	Performance Goals
	Low	Performance-avoidant Goals

Note. Adapted from “A Social-cognitive Approach to Motivation and Personality,” by C. S. Dweck and E. L. Leggett, 1988. *Psychological Review, 95*(2), p. 259. Copyright 1988 by the American Psychological Association.

Effort Beliefs

The divergent goal orientations of students who exhibit different self-theories of intelligence shed a light on a second attribute of Dweck’s (1999) motivational model of achievement: effort attribution. When Nichols (1984) developed his achievement goal construct, he concluded that individuals pursuing “ego involvement” (or performance goals) view effort expenditure as a sign of weakness. In essence, effort is seen as a key indicator of incompetence or low intelligence (Dweck & Bempechat, 1983). Thus for students with a fixed mindset, academic ability is demonstrated through low-effort success and the outperformance of peers (Dweck, 1999). For example, students agreed with statements like “if you’re not good at a subject, working hard won’t make you good at it” (Blackwell et al., p. 250). The findings by Blackwell and her colleagues suggest that an individual’s inability to overcome challenge is influenced by the belief that effort does not promote intelligence. In contrast, those students who view intelligence as malleable typically view effort expenditure as a sign of forward progress towards increasing ability and competence (Diener & Dweck, 1978; Hong et al., 1999).

Failure Attribution

Though the bifurcation resulting from the different mindsets portray two very different types of students – those who hope to *prove* ability versus those who seek to *improve* ability – each type of student may experience success. Grant and Dweck (2003) found that college students with a fixed mindset who exhibited little difficulty with the material were just as likely to succeed as their counterparts. However, in the face of difficulty and failure, studies have demonstrated divergent paths for the two self-theory types. Specifically, entity theorists demonstrate a helpless response pattern whereby individuals with a fixed mindset view their difficulty as indicative of either low ability or factors outside their control (Diener & Dweck, 1978, 1980; Licht & Dweck, 1984). This helpless response pattern in turn encourages students with a fixed mindset to blame their failures on external causes or treat the difficulty as insurmountable. Blackwell et al. (2007) found that these students, when contemplating future strategies for success, would ascribe to negative strategies to avoid the demonstration of failure or expenditure of effort in the future. In contrast, when faced with failure, students holding a growth mindset tend to account for this failure differently from those with fixed mindsets. These students attribute failure to a lack of sufficient effort (Diener & Dweck, 1978, 1980; Licht & Dweck, 1984). For incremental theorists, situations rife with difficulty provide opportunities for increased effort and therefore more opportunity to learn (Dweck & Sorich, 1999; Mueller & Dweck, 1998). Looking forward to the future, these students choose strategies that connote a need for increased effort (Blackwell et al., 2007).

While students holding a growth mindset choose to believe a lack of success can be overcome with remedial action or increased effort (Diener & Dweck, 1978, 1980; Licht & Dweck, 1984; Hong et al., 1999), students who believe intelligence is fixed tend to choose counterproductive methods to remedy success. Rather than work harder, students with fixed mindsets try to cope with their failure through lying and cheating. Anderman, Griesigner and Westerfield (1998) found that for high school students, self-beliefs regarding their school's perceived high concern with performance moderately correlated with the increased aptitude to cheat (r=.31.).

Academic Strategies

According to Dweck's (1999) motivational model of achievement, each of the previously described beliefs or factors contribute to strategies that students utilize for success. These strategies may include any number of behaviors, ranging from increased studying to supplemental instruction, yet students choose strategies that correspond with their self-theory. The differentiation between the types of strategies employed is usually marked by valence. Students who hold an entity or fixed mindset often develop *helpless response patterns*, choosing strategies for success that are counterproductive to learning (Dweck and Master, 2009). Incremental theorists, on the other hand, develop *mastery-oriented* responses, or strategies that promote success.

Students holding a fixed mindset are more likely to exhibit helpless response patterns such as increased anxiety over their performance when compared to students with growth mindsets (Cury, Da Fonseca, Zahn, & Elliot, 2008). In an experimental study that assessed the degree to which theories of intelligence (i.e., fixed vs. growth) affected the IQ test performance of adolescents, Cury et al. found that students with a fixed mindset were highly correlated with the propensity to worry over their performance (r=.41) and were less likely to take advantage of a remedial opportunity that would help them succeed on the test (β=-.34). Similarly, Nussbaum and Dweck (2008) found that college students who held a fixed mindset were more likely to choose a downward comparison strategy, whereby they sought out examples of other students' mistakes versus other students' achievements. In their study, students completed an engineering exam and were then primed by being told that they did poorly on the exam. Students holding both types of self-theories were then given the opportunity to review other students' work. As a result, students with a growth mindset consistently sought out work from those students that scored better than they did on the test. In contrast, students with a fixed mindset sought to review work from students who had reported a worse score. Both of these studies suggest entity theorists choose strategies for success that leave room to adequately explain failure should it arise.

Supporting Research

If Dweck's (1999) motivational model of achievement is correct (a model that focuses on the impact of mindsets on academic achievement), then the mindsets that students embody should correlate with the motivational variables and behaviors previously described and ultimately affect learning outcomes. It should also hold true that if a causal relationship exists between implicit theories of intelligence and academic achievement, empirical manipulation of these mindsets should alter the academic outcomes of students as well. A number of studies have sought to demonstrate these relationships. This section first summarizes important correlational studies of mindsets and motivational variables and then reviews two experimental studies that have explored the causality between mindset and achievement. The section concludes with what is believed to be the first and only attempt to fully assess Dweck's motivational model, a study conducted by Blackwell, Trzesniewski, and Dweck (2007).

Correlational studies. In one of her first studies concerning student's implicit theories of intelligence, Dweck and her colleague (Bandura & Dweck, 1981; as described in Paris, Olson, & Stevenson, 1983) sought to identify the academic behaviors and goals of elementary-aged students when presented with a problem-solving task. The researchers hypothesized that the dichotomous mindsets of incremental and entity theorists would relate to the ways these students thought about and approached these types of tasks.

Students were first asked to respond to three questions that, when factored together, formed a measure of the students' implicit theories of intelligence: "You have a certain amount of intelligence and you really cannot do much to change it," "Your intelligence is something that you can't change very much," and "You can learn new things, but you can't really change your basic intelligence." Rated on a 6-point Likert type scale ranging from 1 (strongly agree) to 6 (strongly disagree), these questions were developed by the authors to assess whether students believe intelligence is malleable or fixed. The children were labeled entity theorists if they obtained a mean score of 3.0 or lower on the scale, while children with mean scores of 4.0 and above were labeled as incremental theorists. To increase the rigor of the study, the approximately 15 percent of respondents who scored between 3.0 and 4.0 on the scale were removed from analysis. Bandura and Dweck concluded that scores in this range were too diffuse for classification into either of the implicit theory categories. The remaining 85 percent of responses were evenly distributed across the implicit theories scale.

Once the students were classified as either incremental or entity theorists, they were then asked to perform a series of problem-solving tasks that progressively grew in difficulty. Before performing the task, the students were first trained by the researchers to understand how to effectively answer the questions. The students were then asked a series of questions concerning the upcoming exercise. Students were asked about their performance expectations, goals, concerns, and potential responses to various potential outcomes.

The study confirmed the authors' hypothesis that incremental and entity theorists would approach achievement opportunities in qualitatively different ways. Incremental theorists reported concerns that the problems might be too easy or that they would not learn from solving the problems. Entity theorists – in contrast – reported concerns about the potential for making mistakes and how the researchers might perceive these mistakes.

When asked how they would feel if the problems were easy and could be completed quickly, incremental theorists more often reported that they would feel bored or disappointed, while entity theorists reported they would feel a sense of pride or relief.

This study was a critical stepping-stone in Dweck's development of a motivational model of achievement. First, the findings by Bandura and Dweck (1981) suggest that there is a rational for classifying students as either an incremental or entity theorist. Second, the study demonstrated that mindsets relate to various other motivational variables including goal orientation, failure attribution, and academic strategy preferences – three key relationships in Dweck's (1999) model.

In a similar study, Bempechat, London, and Dweck (1991) explored the relationship between student mindsets and one's ability to recover from failure on an achievement task. The authors were interested in understanding student motivation after failure outcomes, noting several studies that suggest debilitating motivational tendencies are typically uncorrelated with student skill or intelligence (Crandall, 1969; Dweck & Licht, 1980). As in the prior study, fifth-grade student's mindsets were measured according to Dweck's three-item implicit theory of intelligence scale, and each student was classified as an incremental or entity theorist. One month later, these students were then taught how to solve a problem-solving task of increasing difficulty whereby participants manipulate two sets of nested inverted cans that rest on wooden pegs to match a displayed configuration presented by the experimenter. As each task is completed, the next task grows progressively harder. After students reached their upper capacity, whereby they could solve only one out of three problems correctly, the students were given three nearly insoluble problems. Those students who solved the problems by cheating were informed of their mistakes. Immediately after the failure experience, the students were then given four problems at their upper capacity, and the time taken to complete the tasks was recorded. The researchers found that in comparison to incremental theorists, entity theorists took significantly longer to complete these solvable tasks following a failure experience. In other words, the act of failing had an increased probability of inducing debilitating motivation in students with fixed mindsets over those with growth mindsets.

Seeking to integrate an early version of Dweck's motivational model (see Dweck & Leggett, 1988) with attribution theory, Hong and her colleagues (1999) conducted two studies with undergraduate students to explore the relationship between mindset, effort versus ability attribution, and behavioral responses to failure. The authors hypothesized that implicit theories of intelligence would predict either effort or ability attributions, and that these attributions would mediate mastery-oriented coping. In the first study, 97 undergraduates were classified as incremental or entity theorist by Dweck's implicit theories of intelligence scale. After completing the measure, the students were then asked to complete a 90-item conceptual ability test. Despite the actual score received on the test, each student was provided negative feedback. Students were then asked to make attributions for the poor performance by indicating the importance of effort, ability, luck, and skill. This was done by assigning each factor a weight, where the most important had the largest weight and the least important the smallest weight. While both entity and incremental theorists ascribed similar weights to ability, incremental theorists significantly attributed more weight to effort than did entity theorists. These findings suggest that students with a growth mindset demonstrate a greater focus on effort than their counterparts.

In a second study, Hong and her colleagues (1999) went a step further by suggesting that incremental theorists, in light of their propensity to focus on malleable aspects of performance, may be more apt to engage in remedial action in challenging situations. One hundred and sixty-eight entering freshman at a university in Hong Kong answered a survey where they were first told that English proficiency was very important for academic success. The survey then asked how likely they were to take a remedial English course, indicating their likelihood on an 11-point Likert-type scale ranging from 0 (certainly no) to 10 (certainly yes). The students were also asked to list those classes in secondary school where they received an A or B, making the assumption that if English was not listed, they must have received a C or lower. Finally, the students filled out the implicit theories of intelligence measure. Results from Hong et al.'s study indicated that while high performing entity and incremental theorists displayed the same amount of intention to take a remedial English course, low performing incremental theorists were nearly twice as likely to take a remedial English course to improve their performance when compared to low achieving entity theorists. One of the most important findings of this study was that entity theorists were not as inclined to take remedial courses, even if they believed that their future success relied on these skills, suggesting that believing intelligence is fixed can lead to helpless patterns of behavior.

Finally, a study by Robins and Pals (2002) assessed the causal relationship between mindsets, goal orientation, helpless versus mastery response, and self-esteem changes among university students as part of a longitudinal study of self-esteem and personality development in college. Their sample included 508 undergraduate students who matriculated to the University of California at Berkeley in 1992, each of whom began the study as freshmen and were assessed annually until their graduation.

As part of the study, students reported their mindsets according to Dweck et al.'s (1995) implicit theories scale in their second, third, and fourth years of school. Students' goal orientation was also assessed during these years using the Patterns of Adaptive Learning Survey's Goal Orientation Scale (GOS; Midgley et al., 1998). The GOS measures a student's tendency to assume a mastery or performance goal orientation in achievement related contexts. In order to assess the causal attributions for their academic achievement, the participants in their second, third, and fourth years were asked to weight the following factors according to how they believed each was responsible for their success or failure: ability, effort, study skills, luck, the ability of other students, course difficulty, and pressure to perform well from family and peers. These weights combined to create a helpless versus mastery scale. The students also completed the Positive and Negative Affect Scale (PANAS; Watson, Clark, & Tellegen, 1988) to rate how they felt about their academic performance. The PANAS includes a positive valence option (e.g., proud, excited, determined) and a negative valence option (e.g., upset, scared, guilty). Students' responses to failure were assessed using an eight-item scale, where four questions measured helpless responses (e.g., "When I fail to understand something, I become discouraged to the point of wanting to give up") and four questions measured mastery-oriented responses (e.g., "When something I am studying is difficulty, I try harder"). Students rated their agreement with each item based on a 5-point Likert-type scale (1 = not very true of me; 5 = very true of me). Finally, the 10-item Rosenberg

(1965) Self-Esteem scale was used to measure the change in self-esteem over each year of each student's tenure.

A number of discoveries found in the Robins and Pals (2002) study are important to note. First, undergraduate students did not demonstrate any propensity to increase or decrease on the mindset scale over the course of their college tenure. According to Robins and Pals, this suggests that the college experience itself does not produce "normative mean-level change" in student mindsets (p. 321). This evidence supports the claim that mindset schemas are developed in younger years and are maintained through much of early adulthood (Dweck, 2006). Second, findings from the study reveal that mindsets are highly correlated with each of the hypothesized motivational variables measured by the study: goal orientation, achievement attribution, affective response to failure, and behavioral responses to challenge. These findings were not surprising given previous research concerning these relationships. However, when subjected to path analysis to reveal the relationship between these variables and student self-esteem, Robins and Pals found that a student's mindset does directly shape a student's goal orientation and achievement attribution, each of which shape behavioral responses to failure and indirectly shape self-esteem (see Robins & Pals, 2002 for path coefficients). While the proposed study is not concerned with self-esteem as an outcome of implicit theories, the findings by Robins and Pals do elucidate causal relationships between mindset orientations and the other motivational variables included in Dweck's (1999) motivational model of achievement.

Experimental Studies. As noted previously, if implicit theories of intelligence are causally linked to academic achievement, it is plausible that academic achievement could be altered as a result of manipulating student mindsets through intervention. In a study to test this hypothesis, Aronson, Fried and Good (2002) examined the effects of a mindset intervention on undergraduate students' academic outcomes. Seventy-nine undergraduates from Stanford University were recruited to participate in a long-distance mentoring program for "at-risk" middle school students. Upon recruitment, the undergraduates were randomly assigned one of three conditions. Students in the first condition (malleable pen pal) received a letter from an at-risk seventh grader who described the difficulties he or she was having at school. After reading these letters, the undergraduates were asked to write a reply that would encourage the middle-school student to apply effort and work hard, despite their difficulties. They were told to stress that intelligence is not finite, but that it can grow with effort and work. Students in the second condition (control pen pal) also received similar letters from middle school students, however, the participants were asked to write a reply that emphasized focusing on one's strengths and abilities as keys to success. Students in the third condition (non pen pal) did not participate in the intervention as a non-intervention control, yet the students in all three conditions completed measures at the end of the program that captured mindset orientation, the degree to which they enjoyed academics, and their end-of-course grades.

The writing task was designed to persuade students in the malleable pen pal condition that intelligence was not fixed but expandable. After writing these letters, students in both the malleable and control pen pal conditions were then asked to write a second letter to a new pen pal 10 days later. As part of a third intervention, nearly 20 days after writing the first letter, participants in the two pen pal conditions were asked to adapt their letters into a speech to be performed in front of the other participants. These three interventions were developed so that each would incrementally reinforce the assigned belief of intelligence to the students.

Results from the study indicate that students assigned to the malleable pen pal condition had a greater propensity to believe that intelligence was malleable when compared to students in both the control pen pal condition and the non pen pal condition. Students who had been reinforced with the concept that intelligence was malleable also reported higher rates of enjoyment of academics when compared with participants in the control groups. And when the authors compared the students' grades in the following semester, they found that students in the malleable condition had earned a higher GPA in comparison with students in both control groups, giving credence to the argument that students' beliefs about intelligence can be manipulated.

A second study by Good, Aronson, and Inzlitch (2003) sought to build on these findings by testing their hypothesis among women and racial minorities enrolled in seventh grade classes in a rural school district in Texas. They hypothesized that students who were taught to understand intelligence as malleable (incremental condition), taught that students can bounce back from difficulty (attribution condition), or taught a combination of both (combined condition) would earn significantly higher scores in math on a standardized test than students who were taught about the perils of drug use (control condition). The authors recruited 139 students in an introductory computer skills class to participate in the study, and each were randomly assigned to one of the four conditions. As part of their culminating project in the computer skills class, each student was required to design his or her own webpage. Each student was told that he or she would receive a college mentor that would help craft the message of the webpage the middle-school student was to create.

Students assigned to each of the four conditions were visited by their mentors twice over the course of the school year. In addition, the mentors sent weekly emails to the students. These visits and emails served three purposes: first, the mentors acted as counsel for the students regarding the difficulties experienced when transitioning to junior high school; second, the mentors explicitly taught the experimental message assigned to the condition; and third, the mentors helped the students craft the web pages for the final product, informing the students that the web page would be used as a public-service announcement for the message taught within the condition. After the conclusion of the intervention, students' math achievement scores were analyzed using a statewide standardized test taken by all seventh-grade students at the end of the year. Results from the study suggested a significant main effect for both condition and gender, and a moderating effect of gender by condition interaction. Both boys and girls in all three experimental conditions (malleable, attribution, combined) scored significantly higher on the math section of the standardized test than the control group. Similarly, females who participated in one of the three experimental conditions achieved higher scores than females in the control group. Finally, the achievement gap that was evident in the control group (males significantly achieved higher math scores than females) was virtually erased by participation in one of the three experimental groups.

In summary, results from both the Aronson, Fried and Good (2002) study and the Good, Aronson, and Inzlitch (2003) study suggest that mindsets can be altered through intervention to have an effect on future academic outcomes. This evidence suggests that there may be an underlying relationship between implicit theories of intelligence and academic achievement.

Full meditational model tested. To test this hypothesis, Blackwell, Trzesniewski, and Dweck (2007) sought to test Dweck's (1999) model in its entirety. In their study, Blackwell and her colleagues recruited 373 students in four successive matriculating seventh-grade cohorts at a public school in New York City and followed these students for two years. At the beginning of their first semester in their seventh grade year, each participant filled out a motivational questionnaire which assessed the students' mindsets and Dweck's four hypothesized motivational variables: goals, beliefs about effort, failure attribution and achievement strategies. The researchers then gathered data concerning the students' mathematical achievement. Scores on a citywide standardized achievement test taken at the end of the students' sixth grade year were used as a baseline for achievement. The researchers then collected math grades from the fall semester of the seventh grade year and each subsequent semester through the students' eighth grade year. All participants in the study enrolled in the same math courses with the same mathematics instructors (in each cohort, but different instructors between cohorts).

The authors' analysis of the collected data began with an assessment of the relationship between mindset and academic growth trajectories. Using hierarchical linear modeling, the authors regressed the mathematical outcome of students each semester from seventh through eighth grades on the average change per time the math achievement scores were collected in the first level. In the second level, mathematical growth trajectories were regressed on one's implicit theory of intelligence and one's cohort (as a control for not having had the same teacher between cohorts). The results of the regression model demonstrated that there was no main effect of change in grades across the two-year span, nor was there a main effect of mindset on the grades in the first term of seventh grade. However, Blackwell and her colleagues did uncover a significant causal relationship between mindset and change in grades over time. For each consecutive math term, mindset interacted with time to produce changes in math achievement.

Having discovered this relationship, Blackwell, Trzesniewski, and Dweck sought to determine why mindsets affect achievement outcomes and how the four proposed motivational variables might mediate this relationship. To do so, the authors continued their analysis through two complimentary tests of mediation: exploratory factor analysis and latent variable path analysis

Exploratory Factor Analysis. The authors first assessed all of the items that comprised each motivational construct using exploratory factor analysis. After saving the first unrotated factor score, all items except four loaded above .30. The factor itself accounted for 31.79% of the shared variance between the four motivational constructs. The authors then included the single factor in the previous regression equation. Having done so, the effect of mindsets on change in grades was reduced from significant to not significant, demonstrating a mediating effect of the combined motivational variables.

Latent Variable Path Analysis. The authors then employed latent variable path analysis to test the fit of their hypothesized model. In accordance with prior research, the specifications the authors included in their model assumed an incremental mindset would influence adoption of positive effort beliefs and learning goals. These factors in turn would influence students to adopt fewer ability and helpless attributions and choose positive academic strategies. Finally, adoption of these strategies would lead to improved grades. Growth curves of students' mathematical achievement over four semesters between seventh and eighth grades were used as the outcome variable. The final full model demonstrated adequate fit to the sample data, and all paths were found to be significant. According to Blackwell et al., the final model suggests:

> … (a) learning goals mediate the relation between incremental theory and positive strategies, (b) positive strategies mediate the relation between learning goals and increasing grades, (c) effort beliefs mediate the relation between incremental theory and helpless attributions, (d) effort beliefs mediate the relation between incremental theory and positive strategies, (e) helpless attributions mediate the relation between effort beliefs and positive strategies, (f) positive strategies mediate the relation between effort beliefs and increasing grades, and (g) positive strategies mediate the relation between helpless attributions and increasing grades" (see figure 4; pp. 252-253).

Believed to be the first and only test of Dweck's (1999) full motivational model of achievement, this study suggests that mindsets and the motivational variables of effort beliefs, failure attributions, and achievement strategies fit well as an integrated causal model that affects achievement trajectories among students in junior high school. As noted previously in this chapter, while mindsets had a direct effect on goal orientation and an indirect effect on strategies through the mediation of goal orientation, results from other studies suggest this relationship may be spurious. There is thus a need to further explore this model's efficacy, both in terms of the factors included, and at a different level of education.

Summary. Taken together, much of the research regarding mindsets and their effects on motivation and achievement provide data to support Dweck's model. However, no studies have employed Dweck's model to understand how the intrapersonal motivation of college students leads to academic achievement. Research assessing student mindsets and other motivational variables at the beginning of a semester prior to receiving graded feedback from a professor may illuminate how students use intrapersonal motivation to achieve academically in a challenging course. Other than the work performed by Blackwell and her colleagues, few studies have sought to analyze these relationships outside of a laboratory setting, and no studies have sought to analyze the full mediation model at the collegiate level.

Mapping Dweck's Model to Weiner's Attribution Theory

According to Weiner's (1986) intrapersonal attribution theory, causal attributions influence the activities and behaviors that individuals select and engage in when facing achievement opportunities. This is accomplished by assessing the locus, stability, and controllability of past attributions. Similarly, Dweck's (1999) motivational model of achievement assumes that one's goal orientation, beliefs about the utility of effort, and understanding of failure all contribute to a student's choice of mastery-oriented or helpless strategies that promote or inhibit academic success. The similarities between these two models suggest each of Dweck's motivational constructs (goal orientation, effort beliefs, and failure attributions) inform how students analyze the three dimensions of causality for prior achievement outcomes.

As noted previously, mindsets serve as causal antecedents that shape the way students analyze causal attributions. The patterns for analysis, or the way students think about locus, stability, and controllability, are derived from the differing goal orientations, effort beliefs, and failure attributions that entity and incremental theorists adopt. Table 3 lists each of the causal analysis dimensions in Weiner's (1986) attribution model. The motivational constructs in Dweck's model that correspond with these dimensions are also included, as are the resulting psychological determinants of behavior (and their underlying psychological consequences as a result of analysis).

Table 3.

Weiner's Causal Dimensions, the Corresponding Motivational Constructs in Dweck's Motivational Model, and the Resulting Psychological Determinants

Causal Dimension	Motivational Construct	Psychological Determinant/Consequence
Locus	Failure Attribution	Value Pride Self-Esteem
Stability		Expectancy
Controllability	Goal orientation; Effort Beliefs;	Value Shame Guilt

Note. Stability is unaccounted for in Dweck's (1999) motivational model of achievement.

The goals that incremental and entity theorists adopt provide a framework for how students view the controllability of future academic outcomes. Students with a growth mindset believe they have the ability to learn new material and can control whether or not they learn. According to Dweck's model, these students adopt mastery goals because they believe their learning can be controlled. Fixed mindset students, on the other hand, believe outcomes are due to ability. This is uncontrollable and therefore a foregone conclusion that they will adopt performance goals to demonstrate this ability. Similarly, students' beliefs about the utility of effort also influence causal attributions by defining controllability. Incremental theorists believe they can control outcomes through employed effort, while entity theorists believe one's ability to control outcomes through effort is futile.

Of course, both incremental and entity theorists fail from time to time. Yet when faced with failure, differing mindsets affect the way students use locus to assess the cause of failure. Incremental theorists tend to believe their failure resulted from lack of effort. Thus, the incremental theorist believes the locus of causality to be internal. Entity theorists who attribute failure to lack of ability believe the outcome was due to circumstances outside their control. Because they believe there is nothing that can be done to change intelligence, external factors such as degree of difficulty or fate control the final outcomes.

While Dweck's model seemingly accounts for locus and controllability – the two dimensions that estimate the value of future outcomes – no construct serves to analyze stability. Given the research that suggests one must analyze stability in order to make predictions of expectancy, Dweck's model may benefit by an additional measure that serves in this capacity.

Academic Self-perception as Causal Antecedent Promoting Stability and Expectancy

In Dweck's (2006) most recent reflections on mindsets and motivation, she argues that praising students' abilities promotes the adoption of performance goals. She contends that both parents and teachers should praise student effort instead of ability. For Dweck, attribution, rather than self-perception, plays a larger role in achievement motivation (Dweck, 1999). Yet students who matriculate to universities may find that the challenge they are met with as part of the collegiate environment is above and beyond any challenge they have encountered so far. Self-appraisal and reflection on one's abilities may be necessary for motivation in such circumstances. In a review of the literature concerning the relationship between self-perceptions and college readiness, persistence, and achievement, Pascarella and Terenzini (2005) present evidence that suggests academic self-perceptions in the forms of self-concept and self-efficacy play one of the most important roles in the selection of and success in college. The self-appraisal of what is possible at a college or university plays an important role of expectancy in student motivation in college.

Two sub-constructs of academic self-perception, self-concept and self-efficacy, are foundational to self-appraisal and play a significant role in motivation and academic achievement (see Marsh & Craven, 2006; Schunk & Pajares, 2009). As personal determinants in Bandura's (1997) triadic reciprocal causational model, each interacts to various degrees with behavioral and environmental determinants to promote individual behaviors. Mistakenly, these concepts are many times used synonymously with one another. Yet each is unique – formed and put to use in ways specific to its character. *Self-concept* is understood as self-perceived competence in both general (e.g., academic, athletic) and specific domains (e.g., mathematics or writing) (Marsh & Craven, 1997). Bandura (1995) describes *self-efficacy* as "the beliefs in one's capabilities to organize and execute courses of action required to manage prospective situations" (p. 2). These in turn differ with respect to the psychological domain from which they are composed. Hughes, Galbraith, and White (2011) suggest self-concept weighs competence based on the affective assessment of prior experience, (am I a good quarterback?), while self-efficacy primarily deals with cognitive perceptions of competence (can I throw a touchdown"?) While the affective component may be strong, self-concept too draws upon a competence-based component (Marsh, Byrne, & Yeung, 1999). In their work concerning self-knowledge and its effects on education, Pajares and Schunk (2002) offer a framework for distinguishing between the two constructs. Self-concept reflection asks "being" questions (e.g., Am I a good student? Do I succeed at math?), while self-efficacy asks "can" questions (e.g., Can I make and A? Can I perform mathematical functions?). Differentiating between the two in this way sheds light on how each affect motivation in different ways, and how each concept is best measured.

Academic Self-Perception and Academic Achievement

While research has consistently shown that the student's academic self-concept becomes more positive during the college years (Astin, 1993; Graham & Cockriel, 1997; Kezar & Moriarty, 2000), research into the causal relationship between academic self-concept and academic achievement is sparse. Studies out of the Self-concept Enhancement and Learning Facilitation Research Centre have demonstrated reciprocal positive effects between academic self-concept and academic achievement (Marsh, 1990; Marsh, Byrne, & Yeung, 1999; Marsh & Craven, 1997). Marsh (1990) found that among a sample of 1,456 high school students, reported grade point averages were significantly affected by the students' prior academic self-concepts. Holding constant the previous year's grades, grades in the following years could be attributed to the students' academic self-concept (β_{yr1}= .22; β_{yr2} = .20). In a meta-analysis on the subject, Valentine and DuBois (2005) found that in 90 percent of the studies reviewed, academic self-perception was positively related to subsequent achievement.

Research regarding the influence of self-efficacy on academic achievement is far more ubiquitous than that of self-concept's role, suggesting measures of self-efficacy can be used to significantly predict academic performance (Bandura, 1997; Diseth, 2011;

Zuffiano et al., 2013). Self-efficacy has also been found to influence academic effort and college persistence (Schunk, 1989; Zeldin & Pajares, 2000). Performance in specific academic subjects is also improved through enhanced self-efficacy in corresponding subject domains, such as writing (Schunk 1991; Shell, Murphy, & Bruning; 1989) and mathematics (Pajares & Miller, 1994; Pietsch, Walker, & Chapman, 2003; Skaalvik & Skaalvik, 2011).

While extensive research has linked measures of self-concept and self-efficacy to academic achievement, most only demonstrate correlations between the variables. To explore the causal relations between these constructs, Skaalvik and Skaalvik (2011) designed two longitudinal studies that asked whether academic self-perceptions of mathematical competence predicted subsequent achievement over and above the prediction that could be made by prior achievement alone. They hypothesized that measures of self-concept and self-efficacy influence academic achievement, and that these relationships were mediated by a student's goal orientation, interest, or self-esteem.

The two studies performed by the authors recruited 246 middle school and 484 first-year high school students in Norway respectively. In both studies, baseline grades from mathematical exams were collected at the end of the school year prior to the beginning of the study. Grades from standardized math exams conducted at the end of the study served as the outcome variable. At the beginning of the school year, self-concept was measured by the Self-description Questionnaire II (Marsh, 1990) employing a 5-point Likert-type scale. Self-efficacy was measured by a five-item scale that asked the participants to indicate how certain they were that they would receive a grade better than a 1, better than a 2 etc. in mathematics (Norwegian schools assign grades on a 6-point scale, one being the lowest and six being the highest). To analyze their results, the authors employed structural equation modeling to analyze the efficacy of their theoretical models.

Statistical analysis in both studies demonstrated that measures of self-efficacy and self-concept were significant indicators of a latent math self-perception construct, and that this construct significantly mediated the relationship between prior academic achievement and future academic achievement. The authors' first step was to run a confirmatory factor analysis to determine if the effect indicators of self-concept and self-efficacy loaded onto a shared factor of academic self-perception. Because the authors employed composite scores for self-concept and self-efficacy, the model needed additional variables to be an over-identified model. To compensate, Skaalvik and Skaalvik introduced a prior achievement measure (grades collected before self-concept and self-efficacy were measured) and a post achievement outcome (grades collected after the survey). Allowing the academic self-perception factor to covary with both achievement measures, they were able to confirm a strong and distinct relationship between academic self-perception and the two effect indicators of self-concept and self-efficacy. In the first study among middle school students, standardized results from the confirmatory factor analysis suggested a one standard deviation change in self-perception influenced a .81 standard deviation change in self-concept and a .78 standard deviation change in self-efficacy. In the high school study, the effect of self-competence on the indicators was even greater, where a one standard deviation change in self-perception influenced a .87 and .86 standard deviation change in self-concept and self-efficacy, respectively.

The authors then sought to measure their model through latent variable path analysis. In both studies, prior achievement had high correlations with future achievement (*r* = .81 and .65 respectively). When the academic self-perception construct was introduced, the direct effect of prior achievement on future achievement was either diminished (middle school study) or was non-existent (high school study), while indirect effects mediated through academic self-perception were significant (B = .33 and .57 respectively). When constructs of students' interest, goal orientation, and self-esteem were added to the model, the authors were able to achieve appropriate model fit. However, these three constructs failed to mediate the effect of academic self-perception on future academic achievement.

Proper Measurement of Academic Self-Perception

When proposing a measure of academic self-perception, many researchers note a difference in generality between the two sub-constructs of self-concept and self-efficacy, where the predictive utility of self-concept is maximized in more general domains while self-efficacy is more predictive with increased specificity of the measured behavior (e.g., perceived competence in mathematics versus quadratic equations, science versus photosynthesis) (Marsh et al., 1991, Pajares & Miller, 1994, Bandura, 1997). With regards to the higher generality of self-concept, and because the argument is made that self-concept requires reflection on one's self-efficacy (Bong & Clark, 1999), many researchers will instead utilize a higher order factor of self-perception that includes both constructs (Skaalvik & Rankin, 1997). To understand the efficacy of this methodology, this section reviews two studies that test this practice.

In their study seeking to compare the measurement qualities of self-concept and self-efficacy, Hughes and her colleagues (2011) posed two questions: (1) do self-concept and self-efficacy describe distinct features of personality; and (2) at what hierarchical level do the constructs overlap. Utilizing first- and second-order factor analysis, a study of high school students in the UK (N = 778, age M = 15.04), who had responded to two survey instruments (each built specifically to gather either information particular to student self-concept or self-efficacy), revealed several interesting findings. At the first order level, while self-concept and self-efficacy were found to be strong predictors for several domains, the results suggested overlap in three of the 10 domains (see table 4). Of the ten domains, the overlap occurred in self-perceptions in math/science, self-perceptions in good conduct, and self-perceptions in athletics/sports. At the second level, the research found self-concept and self-efficacy overlap in all domains. The authors concluded that the conventional division between the two factors was exaggerated and instead proposed a single self-perception construct to best measure both factors at general domains. For the current study, a first-order measure of self-competency was also deemed appropriate given that the study sought to measure academic self-perception within the STEM curriculum.

A second study conducted eight years prior by Pietsch, Walker, and Chapman (2003) asked similar questions concerning the relationship between self-concept and self-efficacy. These researchers wanted to test their hypothesis that having removed the affective component of self-concept, both the self-concept construct and the self-efficacy construct would load on a single factor of perceived mathematical competence. They also wanted to better understand the predictive utility of both self-concept and self-efficacy.

Surveys were distributed to 416 high school students between the ages of 13 and 16 to measure mathematical self-concept and self-efficacy, then grades from a standardized test score in mathematics were collected. The authors then processed the data via confirmatory factor analysis and latent variable path analysis utilizing LISREL 8.3 (Jöreskog & Sorböm, 1999). The authors noted that, at first-glance, self-efficacy was the only factor to significantly impact mathematical performance. However, LISREL 8.3 frees paths among exogenous variables, so this resulted in a non-significant finding for self-concept. When the correlation between self-concept and self-efficacy was set to 0, even though the data did not pass goodness-of-fit tests, paths of self-concept and self-efficacy significantly predicted mathematical achievement. The authors went on to postulate that re-adding the affect component would only increase the chance that self-concept would have an effect on these gains. In light of their findings, Pietsch and his colleagues concluded that combined measures of self-concept and self-efficacy constructs are indeed appropriate for assessment of academic self-perception.

Table 4

Hierarchical Model of First- and Second-order Factors of Self-concept and Self-efficacy

Second Order Factor	Academic		Behavioral Conduct		Sports & Physical Appearance		Social	
	First-order Factors	**SE/SC/ Both**	**First-order Factors**	**SE/SC/ Both**	**First-order Factors**	**SE/SC/ Both**	**First-order Factors**	**SE/SC/ Both**
	Self-regulated Learning	SE	Good Conduct	Both	Physical Appearance	SC	Friendship	SC
	Communication Arts	SE	Self-regulated Conduct	SE	Athletic Sports	Both	Self Assertive	SE
	Math/Sciences	Both					Job	SC

Note. Adapted from “Perceived Competence: A Common Core for Self-efficacy and Self-Concept?” by A. Hughes, D. Galbraith, and D. White, 2011, *Journal of Personality Assessment, 93*(3), p. 286. Copyright 2011 by Taylor & Francis Group, LLC. Grey shading indicates those factors where self-efficacy and self-concept overlap.

Summary

Current research suggests that mindsets serve as a schema that seeks to understand and make sense of the degree to which intelligence can change. This schema then works as a framework that affects students' goal orientations, beliefs about the nature of effort, the way students understand failure, and ultimately the academic strategies students employ as they approach achievement opportunities. Prior studies suggest the adoption of a growth mindset leads to mastery-oriented goals and behavior, while adoptions of a fixed mindset leads to performance goals and a helpless response pattern. This development of an intrapersonal framework of motivation is supported by Weiner's (1986) attribution theory. At the same time, Dweck's (1999) conceptual model does not properly serve to assess the expectancy of future behavior. Prior research into the nature of academic self-perceptions suggests that this construct plays a significant role in academic motivation and achievement. Furthermore, one's academic self-perception is developed by reflecting on the quality and stability of one's past experiences to predict what will happen in the future. Therefore, inclusion of a measure of academic self-perception might complement the analysis of intrapersonal motivation through the use of Dweck's (1999) motivational model of achievement.

Few studies have sought to understand the effect of mindsets at the collegiate level, and no studies have attempted to assess Dweck's full model among college students. Aronson et al. (2002) observed that instilling a growth mindset in undergraduates was correlated with increases in grade point averages. Robins and Pals (2002) found that entity theorists regularly adopt performance goals and tend to attribute failure to lack of ability, where as incremental theorists adopt learning or mastery goals and attribute their successes to effort. Finally, Blackwell and her colleagues (2007) were the first to test Dweck's full model at the K-12 level. Their longitudinal study of seventh grade children suggests that implicit theories of intelligence have a direct effect on goal orientation and beliefs about effort and an indirect effect on how students attribute cause to failure, academic behaviors, and academic achievement. This tested model serves as a framework for understanding how implicit theories work to form intrapersonal motivation among students.

CHAPTER 3

METHODS

The present study sought to contribute to the understanding of the intrapersonal motivation of today's college students in the pursuit of academic achievement outcomes. Specifically, this line of inquiry explored the causal effects of student mindsets (i.e., implicit theories of intelligence) on specific factors that comprise a framework of achievement motivation including (a) goal orientation, (b) effort beliefs, (c) failure attribution, and (d) achievement strategies that lead to academic achievement (operationalized as end-of-course grades) at the post-secondary level. To provide such insight, a three-stage study was conducted. Stage one of the study sought to validate Dweck's (1999) motivational model of achievement among first- and second-year students enrolled in introductory STEM courses at a highly selective, public, research extensive university in the Mid-Atlantic. The second stage of the study sought to improve the absolute fit of the model by introducing an academic self-perception construct. Stage three considered additional modifications to Dweck's specified model resulting from the findings produced by the first- and second-stage models. This final stage sought to provide the best tenable explanation of how mindsets influence achievement motivation at the post-secondary level. Data to inform the analysis were collected utilizing a self-administered survey. Survey designs are useful for collecting measureable indicators of latent attitudes from a representative sample to inform the understanding of a larger population (Creswell, 2009). End-of-course grades and demographic information were also collected to complete the data set. Analyses were conducted using structural equation modeling (SEM) to estimate and depict relationships among the aforementioned latent factors and the academic achievement criterion. The following sections of this chapter review the research questions, detail the research framework and instrumentation, and outline the procedures for sampling, data collection, and data analysis.

Considerations Regarding a Three-Stage Study

The first recorded test of Dweck's (1999) full motivational model of achievement was originally performed by Blackwell, Trzesniewski, and Dweck (2007). Their assessment of the structural validity of the model sampled a population of junior high school students. Utilizing motivational data and achievement scores gathered from a random sample (N=373), the researchers employed exploratory factor analysis (EFA) and latent variable path analysis (LVPA) to depict causal links between the measures assessed (see Figure 2). According to their findings, the mindsets of students transitioning from sixth to seventh grade directly influenced the adoption of achievement goal orientations and positive beliefs about the utility of effort, and had a positive indirect effect on the attribution of failure to a lack of effort, adoption of mastery-oriented academic strategies, and increased achievement outcomes. While no study has attempted to validate the full mediation model at the post-secondary level, other studies have sought to examine many of the individual hypothesized relationships utilizing samples of college students. Hong et al. (1999), in a study of 97 college students at Hong Kong University, found a direct relationship between having a growth mindset and believing the employment of effort is a positive rather than negative academic attribute. Utilizing a sample of 508 undergraduate students from the University of California at Berkeley, Robins and Pals

(2002) were able to identify direct relationships between theories of intelligence and failure attributions, and an indirect effect on positive academic strategies mediated through failure attributions. Their data also demonstrated that college students with an entity theory orientation had a moderate positive correlation with the adoption of performance goals ($r = .31$) and a moderate negative correlation with the adoption of learning goals ($r = -.25$). However, other studies seeking to model the causal links between mindset, goal orientation, and achievement have not been able to demonstrate the same effects. Dupeyrat and Marine (2005) sampled 76 French students returning to college after a year away from study and found no causal link between implicit theory of intelligence and goal orientation. Spinath & Stiensmeier-Pelster (2001) were able to link theories of intelligence to goal orientation in only one of five correlational experiments among college-aged students. Having demonstrated mixed results, these studies predicate the need for research that seeks to validate Dweck's (1999) full model among college students as originally specified. Stage one of this study fulfilled this need.

To account for the discrepant findings in the literature previously mentioned, the second stage of the study introduced a higher-order academic self-perception construct that includes two sub-constructs: students' academic self-concept and self-efficacy in the specific domains of science, technology, engineering, or math. It was hypothesized that inclusion of this factor (see Figure 3) would increase the absolute fit of Dweck's (1999) motivational model through by moderating effects of goal orientation on adopted achievement strategies. In order to test this hypothesis, it was imperative that Dweck's (1999) *a priori* model first be validated (Mueller & Hancock, 2010). The third stage of this study considered the findings from the first two stages and, in alignment with the theoretical and empirical conclusions of these models, proposed modifications to the achievement motivation model to best explain the influence of mindsets on motivation and achievement at the post-secondary level.

Research Questions

This study sought to answer the following research questions: (a) Do mindsets (i.e., students' implicit theories of intelligence) play a significant role in the motivation and academic achievement of first- and second-year students enrolled in STEM courses at the collegiate level; (b) if so, do these relationships conform to the specified parameters proposed by Dweck's (1999) motivational model of achievement; and (c) does the addition of an academic self-perception factor add to the explanatory power of Dweck's theory?

The inclusion of an academic self-perception construct provided additional room for inquiry in the study. Inclusion of this variable was based on three sets of literature. First, Weiner's (1986) intrapersonal motivation model suggests causal antecedents play a significant role in attribution and motivation. Since mounting research suggests that mindsets acting as a causal antecedent do not fully explain the function of achievement goal orientation in Dweck's (1999) model (e.g., Dupeyrat & Marine, 2005; Stipek & Gralinski, 1996), another causal antecedent may better explain this relationship. The second body of literature suggests there is a shared relationship between the causal antecedent of academic self-perceptions and achievement goal orientation (Dweck and Leggett, 1988; Middleton & Midgley, 1997; Pajares, Britner, & Valiante, 2000) that may account for the spurious nature of goal orientation in Dweck's model. Finally, the literature has overwhelmingly demonstrated a direct causal relationship between the lower order factors that comprise academic self-perception – domain specific self-concept and self-efficacy – and academic achievement (for reviews of the literature, see Marsh & Craven, 2006; Robins et al., 2004). Based on the prevailing research, the present study conceptualized the inclusion of an academic self-perception construct to enhance the analysis of the relationship between mindsets and academic achievement. Inclusion of this factor posed three hypotheses regarding the role academic self-perceptions play in the relationship between mindsets and academic achievement:

> Ho_1 = Mindsets will play a significant role in the motivation and academic achievement of first- and second-year students enrolled in STEM courses at the collegiate level.
>
> Ho_2 = However, Dweck's (1999) specifications will exhibit ill-defined fit among post-secondary students given the limitations expressed in prior research that suggests goal orientation is a poor mediator of the relationship between student mindsets and achievement strategies (e.g., Dupeyrat & Marine, 2005).
>
> Ho_3 = The introduction of an academic self-perception construct will add to the causal explanation of motivation and achievement while increasing the absolute model fit of Dweck's (1999) motivational model of achievement. When introduced to the proposed model, academic self-perception will account for the discrepant relationship between mindset and goal formation.

Research Context

This study sought to examine the mindsets (i.e., implicit theories of intelligence), academic self-perceptions, achievement goal orientations, beliefs about the utility of effort, failure attributions, achievement strategies, and academic achievement of first- and second-year traditionally aged (17 to 20 year-old) undergraduate students enrolled in introductory STEM courses at a highly selective, public university in the Mid-Atlantic. At the time of data collection, the institution composing the sampling frame was classified by the Carnegie Foundation as a "Research Extensive University – Very High Research Activity" (Carnegie Foundation for the Advancement of Teaching, 2014). Considered predominantly residential, the university served approximately 14,900 full-time undergraduates, more than two-thirds of who claimed in-state status during the 2013-14 school year. During this time period, the institution's ratio of women to men was 55 percent to 45 percent, and nearly 60 percent of full-time enrolled undergraduates identified as white in comparison to 12 percent identifying as Asian, 6 percent identifying as Black or African American, 6 percent identifying as Hispanic, and 16 percent identifying as other or choosing not to identify. The targeted institution was also considered a highly competitive institution, admitting only 30 percent of those students who apply for admission (IPEDS, November 2013). In order to ensure respondent confidentiality, the targeted institution is referred to as Mid-Atlantic University or MaU for the remainder of this manuscript.

Description of the Sample

The study utilized both targeted and random sampling techniques to assess the role of mindsets on academic motivation and achievement at the collegiate level. The theoretical target population for this study was traditionally aged, first-and second-year undergraduate students enrolled in introductory STEM courses. The sampling frame employed for this study drew from the enrollment of first- and second-year students at MaU during the spring of 2014. As the study sought to infer characteristics of all first-and second-year undergraduates from a sample derived from a particular institution, coverage error was introduced to the data. To mitigate this coverage error, SEM was employed for analysis. One strength of SEM is its ability to account for coverage and measurement error while simultaneously estimating parameters of a target population (Schumacker & Lomax, 2010). This is achieved by structurally mapping both parameter estimates and error terms associated with those estimates that account for all conceivable alternatives.

In order to collect data regarding the latent factors in both the stage-one and stage-two models, the study's sample was randomly selected from all first- and second-year students enrolled in introductory level STEM courses offered during the Spring 2014 semester at MaU. Introductory level STEM courses provide an optimal environment for assessment of the hypothesized motivational models. According to Grant and Dweck (2003), the causal effects of mindsets on motivation and achievement may only manifest themselves in those courses that present enough challenge to the student, and where outcomes are important enough to sufficiently activate motivational behaviors. Similar conclusions were identified in studies ranging from the performance of concept-formation tasks (Elliot & Dweck, 1998) to solving math problems (Barron & Harackiewicz, 2001). Not only challenging, introductory level STEM courses at MaU serve as prerequisites for many STEM degrees or requisite courses for attainment of a liberal arts degree. In both circumstances, these introductory level courses represent highly important stepping-stones towards degree completion at MaU. Finally, introductory STEM courses more closely emulate the high-stakes academic environment of the high school when compared with other post-secondary curricular offerings

(Mastascusa et al., 2011). Most STEM courses include mid-term and final examinations and employ lecture as the main form of content dissemination. These courses demonstrate a level of pedagogic parity with their high school predecessors and can therefore be hypothesized to evoke similar findings as those demonstrated by Dweck and her colleagues at the K-12 level (see Dweck, 1999).

Participants were randomly selected from enrollment in those courses identified by MaU as introductory level STEM courses (see Appendix A for a list and description of these courses). Enrollment records for the selected courses at MaU composed the sampling frame. Though enrollment in one of the identified introductory STEM courses was voluntary, non-enrollment precluded participation in the study. A random sample generated by the Office of Institutional Assessment (OIA) at MaU culled a sample of 2,000 students from the sampling frame. Ineligible units were identified and removed from the sampling frame before the sample population was selected. Ineligible units included non-traditional students (operationalized by age) and dual enrollments. If students were enrolled in more than one introductory STEM course, they were included in the sample only after one of their enrollments was randomly dropped from the sampling frame. Data concerning respondent demographics and end-of-course grades was gathered from MAU's OIA at the conclusion of the Spring 2014 semester. Responses from 501 participants composed the final sample.

Following the recommendations of Mueller and Hancock (2010), the sample size was determined by the two requirements of SEM analysis: the data must provide (1) proper parameter estimation and (2) sufficient power for relevant tests of model-fit. A general consensus regarding the stability of parameter estimates is to collect at least five cases per parameter when employing maximum likelihood (ML) estimates (Mueller & Hancock). The largest model considered was composed of 37 observed variables (or scales) and 84 estimated parameters (47 regressions and 37 variances). For reliable parameter estimation, the sample needed to be greater that the parameter estimate indicator, P_E= P x 5, or 84 x 5 = 420. To provide sufficient power when testing or comparing the nested models, an *a priori* critical sample size (N_{crit}) was calculated in accordance with the recommendations of MacCallum, Browne, and Sugawara (1996). MacCallum et al. recommend measuring power according to the parsimony of the model, whereby goodness-of-fit estimates for model parsimony are estimated at three levels; perfect fit (RMSEA < .05), close fit (0.5 < RMSEA < 0.8), and not close fit (.08 < RMSEA). The power to correctly estimate parsimony at each fitness level depends on the degrees of freedom for the model and the samples size. For a desired power level of .80, whereby we would correctly reject the null hypothesis 80 percent of the time when the null is false, N_{crit} was calculated at each level of parsimony for the stage-one model specifying Dweck's (1999) proposed parameters (*df* = 520), the stage-two alternative hypothesis model that included the academic self-perception factor (*df* = 619), and comparison of the nested models (*df* = 3). As MacCallum and his colleagues note, the calculated N_{crit} increases as degrees of freedom decrease. As exact fit is rarely observed given the nature of observed data in the social sciences (Schumacker & Lomax, 2010), this study sought to achieve .80 power value at the recommended close-fit level (0.5 < RMSEA > 0.8). To ensure a power value of .80 when comparing the fit of the nested models (*df* = 3), the calculated N_{crit} for the analyses was 575.

Anticipating a response rate of 25 percent, the survey instrument was distributed to a random sample of 2000 students. To incentivize response, respondents were entered into a random drawing for 10 $50.00 gift cards to a leading online retailer. The final sample of 501 respondents afforded a satisfactory ratio of 5.96 cases per parameter but was less than N_{crit} of 575 to ensure sufficient power for testing the differences between the nested models. Therefore, a post-hoc power analysis was conducted after the final sample size (501) was compiled according to the recommendations of MacCallum et al. (1996) and Saris and Satorra (1993) using G*Power 3 (Buchern et al., 2014). The power analysis estimated the power values at exact-fit, close-fit, and not close-fit RMSEA levels according to the final models' degrees of freedom and final sample size of 501. Tables 5, 6, and 7 list the power value estimates for each closeness-of-fit index at an alpha level of .05 and degrees of freedom for the stage-one model, stage-two model, and nested models numbering 254, 326, and 3 respectively. Power value estimates for a stage-three model could not be provided given the post-hoc construction of the stage-three model.

TABLE 5

Power Analysis Estimates for Stage-one RMSEA Test of Fit

MacCallum Test	**MacCallum et al. (1996) Null and Alternative Values for RMSEA Test of Fit**		**Power**
	H_0	**H_a**	
Exact	.00	.05	1.000
Close	.05	.08	1.000
Not Close	.08	.10	1.000

Note. Power Analysis estimates according to Figure 2, Stage-one Hypothesis model (α = .05, df = 254, N = 501)

TABLE 6

Power Analysis Estimates for Stage-two RMSEA Test of Fit

MacCallum Test	**MacCallum et al. (1996) Null and Alternative Values for RMSEA Test of Fit**		**Power**
	H_0	**H_a**	
Exact	.00	.05	1.000
Close	.05	.08	1.000
Not Close	.08	.10	1.000

Note. Power Analysis estimates according to Figure 3, Stage-two Hypothesis model (α = .05, df = 326, N = 501)

TABLE 7

Power Analysis Estimates for Nested Model Difference RMSEA Test of Fit

MacCallum Test	**MacCallum et al. (1996) Null and Alternative Values for RMSEA Test of Fit**		**Power**
	H_0	**H_a**	
Exact	.00	.05	.338
Close	.05	.08	.742
Not Close	.08	.10	.917

Note. Power Analysis estimates for Nested Models (α = .05, df = 3, N = 501)

Tables 8 and 9 provide an overview of the final sample (N = 501) demographic and academic characteristics. *Z* tests were conducted to assess whether demographics of the respondents to the survey were significantly different from the sample provided by OIA. Demographic differences between the provided sample and those who responded to the survey according to race, socio-economic status, STEM major, year in school, and subject domain were non-significant. Similarly, there were no significant differences between the provided sample and respondents regarding their high school GPA, SAT (or ACT equivalent) scores, or earned college credit upon matriculation. However, while women barely constituted more than half of the sample provided by OIA (μ = .507), there was a significant difference in the ratio of women to men that responded to the survey ($\bar{x}$ = .617), $z(N = 501) = 4.913$, $p < .05$.

Table 8

Demographic Characteristics of the Sample

Demographic	Frequency	Percentage
Gender		
Male	192	38.3
Female	309	61.7
Race		
White	361	72.1
Black	21	4.2
Asian	112	22.4
Hispanic Origin	20	4.0
American Indian or Alaska Native	8	1.6
Native Hawaiian or Pacific Islander	2	0.4
Reporting Multiple Races	35	7.0
Socio-Economic Status		
High	339	67.7
Medium	100	20.0
Low	62	12.4
STEM Major		
Yes	397	79.2
No	104	20.8
Year in School		
First-year	359	71.7
Second-year	142	28.3
Domain		
Science	279	55.7
Technology	53	10.6
Engineering	27	5.4
Math	142	28.3

Note. $N = 501$. Participants were allowed to indicate more than one race variable; therefore, the sum of responses to race does not equal 501 responses.

Table 9

Academic Characteristics of Sample

Characteristic	Range	Mean	Standard Deviation
High-School GPA	3.76 – 4.80	4.288	.223
SAT Score (or ACT Equivalent)	1830 – 2360	2091.23	127.544
Earned College Credit upon Matriculation	0 – 35	13.405	9.760
End of Course Grade constituting Sampling Frame	0.00 – 4.00	3.12	.716

Note. $N = 501$.

Instrumentation

This study employed a single questionnaire (see Appendix B) composed of items from five established instruments in the field of educational psychology: (a) the *Implicit Theory of Intelligence Scale for Adults* (Dweck et al., 1995; Dweck, 1999) to determine the extent to which a student holds a fixed or growth mindset; (b) the *Goal Orientation Scales* (from the Pattern of Adaptive Learning Survey, Midgley et al., 1998) to determine a student's propensity to choose learning (or mastery) goals, performance goals, or performance-avoidant goals; (c) the *Effort Orientation Inventory* (Dweck & Sorich, 1999) to measure students' beliefs about the utility of effort, their attributions to failure, and strategies students would choose to seek academic success when faced with failure; (d) the *Self Description Questionnaire III* (SDQ III) (Marsh & O'Neill, 1984) to assess students' perceived self-concept in the domain-specific categories of science, technology, engineering, or math; and (e) the *Problem Solving Self-efficacy Scale* (Bandura, 2006) developed to assess a student's domain-specific self-efficacy. At the permission of the Office of the Vice President for Student Affairs at MaU, demographic data (e.g., age, gender, ethnicity, Pell grant recipient status) was retrieved from university records via MAU's OIA. The survey instrument was compiled and disseminated using Qualtrics (Qualtrics, 2009), a web-based survey development tool that features complex logic, piping, and the ability to export data to various statistical software packages.

Implicit Theories of Intelligence

Implicit theories are core assumptions that reside in our unconscious (Wilson, 2002). Though they do not automatically determine behavior, implicit theories inform the schemas used to promote behavior. Dweck and her colleagues (1995) identified a bimodal implicit theorem that shapes the way individuals conceptualize intelligence: they argued all individuals ascribe to either incremental or entity implicit theories of intelligence; that is, they embody either a growth (incremental) or fixed (entity) mindset. Those with a growth mindset assume intelligence is both malleable and controllable, while those with a fixed mindset believe intelligence is permanent and uncontrollable.

The *Implicit Theory of Intelligence Scale for Adults* (Dweck et al., 1995) was developed to assess whether adolescents and adults ascribe to incremental or entity theories of intelligence. Because these implicit theories are latent constructs that guide social information processing and therefore cannot be directly observed, Dweck and her colleagues formed a three-item scale using a six-point Likert-type response format where students report their level of agreement with each item.

The three measured variables that serve as effect indicators for the mindset scale include: (a) You have a certain amount of intelligence, and you can’t really do much to change it; (b) Your intelligence is something about you that you can’t change very much; and (c) You can learn new things, but you can’t really change your basic intelligence. Those with a fixed mindset demonstrated agreement with the items, while students with a growth mindset disagreed with the statements. Though none of the items depict an incremental theory of intelligence or growth mindset, a study by Henderson and Dweck (1990) concerning the validity of the scale asked respondents to explain why they agreed or disagreed with the items. According to their data, respondents who disagreed with the statements provided clear growth mindset rationales for their responses.

Having conceptualized the measurement scale, Dweck and her colleagues (1995) conducted five studies on the validity and reliability of the instrument. Results from regression analyses including the implicit theory of intelligence scale and other identified factors that hypothetically conflate with student mindsets suggest that the implicit theory of intelligence measure is not altered by measures of social desirability ($\beta = .02$, *ns*), cognitive ability (SAT Scores; $\beta =-11.03$, *ns*), confidence in intellectual ability ($\beta = -.01$, *ns*), self-esteem ($\beta = .39$, *ns*), or optimism in other people ($\beta = .11$, *ns*) and the world ($\beta = -1.71$, *ns*). Reliability estimates for the measurement scale demonstrate Cronbach alpha ratings of .94 to .98, and a test-retest reliability of .80 over a 2-week period.

Academic Motivation

While measures of prior achievement (i.e., standardized admissions tests, high school GPA) hold predictive validity for academic achievement at the collegiate level, these variables account for only a proportion of the variance in students' achievement scores (Pascarella & Terenzini, 2005). In order to explain the remaining variance, educational psychologists have sought to explore student motivation in the classroom. Motivation is a theoretical construct that helps explain the initiation, direction, intensity, persistence, and quality of behavior (Maehr & Meyer, 1997). Motivation in the classroom is understood to stem from the selection of achievement goals and rely on one's perceptions of ability and effort (Graham & Williams, 2009; Weiner, 1979). To measure the latent constructs that compose motivation, the *Goal Orientation Scales* (GOS; Midgley et al., 1998) and the *Effort Orientation Inventory* (EOI; Dweck & Sorich, 1999) were developed.

The GOS measures a student's tendency to assume a learning/mastery or performance goal orientation. Eleven questions compose the scale using a six-point Likert-type response format in which students report their level of agreement with certain statements. The scale includes mastery-oriented statements (e.g., “An important reason why I study is because I like to learn new things”), performance-oriented statements (e.g., “Sometimes I would rather perform well in a class than learn a lot”), and performance-avoidance statements (e.g., “It’s very important to me that I don’t look stupid in class”). Mastery-oriented responses were reverse-scored, and all items were averaged to form a composite score (ranging from 1-6) for descriptive analysis. High composite scores indicated a tendency to select mastery-oriented goals when evaluating paths of achievement. In a meta-analysis of the reliability estimates for the PALS goal orientation scales, Ross, Blackburn, and Forbes (2005) found that among 13 studies that employed the scales at the collegiate levels, alpha reliability estimates ranged between .75 and .93. Jagacinski and Duda (2001), in a study of 393 undergraduates, found that the GOS scale demonstrated high convergent validity: as predicted, the GOS demonstrated significant correlations with a number of measures hypothesized to be positively or negatively associated with task goal orientation among college students. The researchers also found that the correlation between the GOS measures of implicit theories of intelligence was nonsignificant. Therefore, the GOS measures are considered to be appropriate for college-age populations, such as those in this study.

The EOI is composed of three scales that measure students’ beliefs about the utility of effort, their causal attributions for failure, and strategies they would choose to seek academic success in the face of failure. These sub-constructs of motivation and coping allow students to overcome challenges, take risks, and thrive in the face of obstacles (Dweck & Sorich, 1999), and are integral to academic achievement (Dweck, 1999).

Effort beliefs. Based on Weiner's (1986) attribution framework of motivation, the EOI subscale of effort beliefs seeks to measure the degree to which students attribute achievement to effort in comparison to other variables (e.g., ability, luck, mood). The EOI effort beliefs subscale includes nine items that seek to assess the degree to which the respondent believes applied effort leads to beneficial outcomes verses feeling helpless. Items use a six-point Likert-type response format in which students report their level of agreement with each item. The scale includes four positive valence effort items (e.g., "The harder you work at something, the better you will be at it") and five negative valence effort items (e.g., "To tell the truth, when I work hard at my schoolwork, it makes me feel like I'm not very smart"). Responses to the four positive valence effort items were reverse scored, and all items were averaged to form a composite score (ranging from 1-6) for descriptive analysis. High composite scores on the effort beliefs scale indicated a belief that increased effort promotes gains in academic achievement.

Failure attribution and academic strategies. In order to assess those response patterns that are characteristic of students when they face failure, the EOI (Dweck and Sorich, 1999) includes two subscales for measuring a student's response to failure and the strategies the student would undertake immediately following said failure. To assess these constructs according to the research instrument, students were presented with a hypothetical failure scenario then asked to rate their predicted response according to both failure attribution and strategy scales. Respondents were instructed to pretend that the scenario did in fact happen to them and are asked to picture how they would feel and what would they do if the scenario truly happened. The scenario was presented to the research participant as follows:

> Imagine that during your second semester at (MaU), you take an important course in your major. You think you know the subject pretty well, so you study a medium amount for the first quiz. When you take the quiz, you think you did okay, even though there were some questions you didn't know the answer for. Then the class gets their quizzes back and you find out your score: you only got a 54, and that's an F.

The failure attribution scale sought to measure whether the respondents believed either their effort (or lack thereof) caused the failure or the grade was the result of other factors outside their control (helpless orientation). Six items using a six-point Likert-type scale assessed the respondents' helpless orientation by offering reasons why the student would have failed the quiz (e.g., “I wasn't smart enough” or “I didn't study hard enough”). Items range from 1 (*very true*) to 6 (*not at all true*). Effort oriented items were then reverse scored, and all items were averaged to form a composite score (ranging from 1-6) on the failure attribution scale for descriptive analysis. Low scores on the scale represented a belief that students were helpless to prevent failure, while high scores attributed failure to the lack of effort by the respondent.

The academic strategies scale was designed by Dweck and Sorich (1999) to ascertain whether the respondent would engage in positive, mastery-oriented strategies or negative, helpless response patterns after experiencing a set-back or failure. Four items employ a six-point Likert-type scale ranging from 1 (*very true*) to 6 (*not at all true*). Each item included a measure of a student's mastery-oriented or mastery-avoidant strategies (e.g., “I would work harder in this class from now on” or “I would spend less time on this subject from now on”). Mastery-oriented strategy items were reverse scored, and responses were averaged to form a composite score (ranging from 1-6) on the effort strategies scale. High scores represented a propensity to engage in positive, mastery-oriented strategies to overcome failure.

Previously, questions from the EOI subscales were combined in two studies (Blackwell, Trzesniewski & Dweck, 2007; Grant & Dweck, 2003) and administered to both adolescents and young adults. Internal reliability estimates of the EOI scales ranged from Cronbach alpha ratings of .73 to .84, with test-retest reliabilities over two weeks measuring from .71 to .85. In both studies, analysis revealed no discernable effects of order.

Academic Self-Perception

Self-beliefs are theoretical in nature, yet the prevailing assumption in contemporary research suggests individuals' perceptions of their competence play vital roles in achievement tasks. Specifically, measures of academic self-perception have been shown to predict academic achievement in both general content (Bandura, 1997; Schunk, 1989; Zeldin & Pajares, 2000) and specific subject domains (Schunk, 1991; Pajares & Miller, 1994; Skaalvik & Skaalvik, 2011). In doing so, these perceptions form schemas that explain and evaluate past behavior while regulating expectations for future performance (Markus, 1977). As previously reviewed in chapter two, academic self-perception is operationalized as a higher order factor that includes measures of perceived self-concept and self-efficacy. To measure these academic self-perceptions, two instruments were incorporated into the study.

Marsh and O'Neill's (1984) *Self Description Questionnaire III* (SDQ III) was used to measure college-aged students' academic self-concept in a particular STEM domain. The SDQ III includes 13 scales that measure self-perceptions ranging from academic ability to physical appearance. For the purposes of this study, only the academic subscale was used (Cronbach alpha = .89; Leach, Henson, Odom, & Cagle, 2006). The academic subscale consists of 10 questions, half of which are negatively worded. Participants responded to an 8-point, Likert-type scale ranging from 1 (*definitely false*) to 8 (*definitely true*). Negative valence items were reverse coded, and all items were summed to form an academic self-concept score to serve as the academic self-concept indicator regressed onto academic self-perception. Higher composite scores demonstrated higher perceptions of subject-specific (e.g., science, technology, engineering, math) self-concept.

In two studies conducted to measure the construct validity of the SDQ III, no discernable effects of order were revealed, allowing for assessment of a single scale (Marsh & O'Neill, 1984). The academic subscale was designed with the intent of measuring the academic criterion at the domain-specific level. Thus, the subject included in the statement (e.g., mathematics in "I have generally done better in mathematics courses than other courses") was substituted for other subjects such as science, technology, or engineering. For the purposes of this study, the operative subject included in the 10 self-concept items matched the subject domain of the course the respondent enrolled in for consideration in the study.

The *Problem Solving Self-efficacy scale* (Bandura, 2006) is a simple 10-item instrument that was developed to measure a student's perceived ability to answer academic problems in any academic domain. Participants were asked to "rate how certain you are that you can solve the academic problems for [particular subject] at each of the levels described below" (p. 324). Ten levels were then described, from "can solve 10% of the problems" to "can solve 20% of the problems" and so on until the final level "can solve 100% of the problems." For each level, respondents rated their degree of confidence by recording a number from 0 (cannot do at all) to 100 (highly certain can do). For example, a student enrolled in applied mathematics would have been asked to rate his or her certainty of solving academic problems in applied mathematics. A student with a high degree of self-efficacy should have reported high numbers across the 10 item scale, where a student with lower self-efficacy may have reported high confidence for the first items, but reported lower confidence levels as the percentage of problems solvable increased.

Because of an identification issue whereby estimation of the academic self-perception factor could not be estimated with only two effect indicators (self-concept and self-efficacy), the present study employed exploratory factor analysis (EFA) to divide the self-efficacy items into two sub-scales of self efficacy: SE15 representing items 1 through 5 and SE610 representing items 6 through 10. The methodology employed for the EFA and consequent results is reported later in this chapter. Responses to the different items for each scale were summed to provide two scores of domain-specific problem solving self-efficacy ranging from 0 to 500 for. Higher scores on these scales scale represented higher perceived self-efficacy beliefs. Both composite scores served as indicators for the academic self-perception construct in the hypothesized model.

The Problem Solving Self-Efficacy scale was developed by Bandura (2006) in compliance with his guidelines for constructing self-efficacy scales. Because self-efficacy is concerned with perceived skill capability, the items reflect a design to measure a student's ability to specifically answer problems rather than an attitude of general ability. The scale has been utilized several times to assess problem-solving self-efficacy among college students, with Cronbach alpha loadings ranging from .82 to .93 (Mcquiggan, Mott, & Lester, 2008; Mcquiggan & Lester, 2009).

Permissions

Permission for use of the scales included in this study's research instrument was obtained from the copyright holders. As a condition of use, any publications resulting from this study will acknowledge the origins of all instruments. Furthermore, as a condition of use of the SDQ III, data collected according to the perceived self-concept scale was submitted to the SELF Research Centre (Marsh & O'Neill, 1984). Before submission to the SELF Research Centre, the composite data were stripped of information measured by the other subscales and all demographic information other than age and gender. The information provided to the SELF Research Centre will be used only for psychometric evaluation and additional norming of the instrument.

Course Information

Appendix A details the courses that were identified as appropriate markers for the sampling frame of the study. Courses were included in the sampling frame if they were considered an introductory course in a science, technology, engineering or math (STEM) discipline. A course was considered introductory if it met the following three criteria: (a) the course served as a prerequisite for further study in the discipline; (b) the course introduced concepts that inform more advanced coursework; and (c) the course was recommended by STEM departments as part of a first- or second-year curriculum. In total, 46 courses were identified as introductory STEM courses offered during the spring, 2014 semester in which this study was conducted. Combined, these courses had an enrollment capacity of 5,939 from which the survey sample was randomly drawn.

Data Collection

In accordance with federal regulations regarding human research studies, details of the study were submitted to the Institutional Review Board (IRB) for social and behavioral sciences for approval. Secondary approval from the Office of the Vice President for Student Affairs at MaU was also obtained in order to distribute the survey instrument and collect data from a sample of the undergraduate population at MaU. Once approved, the OIA generated a list of names, public student identification codes, the subject domain of the courses in which the students were enrolled, and the e-mail addresses for the sampled students. A pre-notice letter (Appendix C) was sent one week prior to distribution of the survey instrument via email to each member of the sample using his or her institutional email address. Studies have demonstrated that pre-notice letters can reduce the nonresponse error of survey research (Groves et al., 2009). The pre-notice letter informed the sample participants of their selection to voluntarily participate in this research study. Sampled participants were also notified that full participation in the survey would make them eligible for a random drawing of one of ten $50 gift cards from a leading online retailer.

Approximately four weeks after commencement of the semester, an email was distributed to the sample containing an Internet link to the survey instrument. The instrument was customized for each participant according to the subject domain of the course that registered them in the sample frame (e.g., students enrolled in Chemistry courses responded to a survey with items that referenced Chemistry, while students enrolled in Math courses responded to a survey with items that referenced Math). Of the 501 respondents, 284 responded to the science referent survey, 53 responded to the technology referent survey, 41 responded to the engineering referent survey, and 123 responded to the math referent survey. Hosted by Qualtrics (2009), a secure web-based survey development tool, the survey began with an informed consent form (Appendix D) detailing the purpose of the study. The consent form clarified that participation was voluntary, all information would be kept confidential, and the data set would be made anonymous after all variables were added.

Upon consent, each participant was asked to complete the 57-item survey composed of the seven scales previously listed. The estimated time of completion for the research instrument was 30 minutes. Upon completion of the survey, no further action was required from the respondent. Two notices were sent to non-respondents to encourage response. The first notice was sent four days after the survey was distributed. The second notice was sent out one week later. Collection of data from the survey was discontinued after three weeks.

Once the survey data were collected, a data file was prepared and sent to MaU's OIA. The OIA added the respondents' end-of-course grades, demographic information (i.e., age, gender, race, Pell grant status), and prior academic achievement measures to the data file. A member of the office then stripped the student identification codes, essentially making the data anonymous. The data were then securely transferred to the researcher's computer for analysis. Only the principal researcher, the committee chair, and MAU's OIA had access to the data files.

Preparation of the Data for Statistical Analysis

Preparation of the data included a preliminary analysis (including tests for nonnormality and multicollinearity), review of outliers and missing data, and recoding of select variables (e.g., reverse scoring items in such a way that higher values consistently indicated favorable conditions for all effect indicators).

Preliminary Analysis and Tests for Nonnormality and Multicollinearity

The initial analysis of the data set was conducted to inspect the completeness and accuracy of responses. Descriptive statistics were analyzed using SPSS 22 (IBM Corp., 2013). Frequencies, means, standard deviations and ranges were computed to test for errant entries in the data. Due to the accuracy of the data collection software, no data entry errors were identified in the sample data. Tests for nonnormality for each measured variable were also conducted, specifically noting possible skewness or kurtosis in the data. Multicollinearity was also measured by running collinearity diagnostics. SPSS provides two values that indicate possible multicollinearity: tolerance and variance inflation factor (VIF). Table 10 provides an overview of the univariate normality and multicollinearity diagnostic statistics for the sample data collected in this study.

The calculated univariate normality statistics suggested the sample data demonstrated a high level of skewness and kurtosis for a majority of the measured variables. Only one of the 34 variables used in the assessment of the stage-one model was nonsignificant for either skewness or kurtosis (LEARN4). This can be problematic given the underlying assumption of normally distributed data for ML estimation. Bollen (1989) suggests that problems of skewness are allayed with large sample sizes over 500 given that skewness more appropriately describes the tails of the distribution rather than the central portion of the distribution. Fortunately, the final sample size of 501 for this study met this criterion. To mitigate the kurtosis issues found in the data, the study followed the recommendations of Finney and DiSteffano (2013) by using the Satorra-Bentler (S-B) scaled-χ^2 and robust standard errors scaling method when estimating and testing the model fit. A discussion of the S-B scaled-χ^2 scaling method is provided later in this chapter.

The data also suggested a certain degree of multicollinearity among several of the measured variables. Decisions regarding the use of highly correlated variables (tolerance approaching < .20 or VIF approaching 5; bivariate correlations > .85; Schwarz, Schwarz, & Black, 2014) were re-assessed against theory to decide if variables needed to be altered (e.g., fixed loading; dropped from analysis). The variables of most concern included the three implicit theories of intelligence indicators (ENT1 – ENT3). From an analytical standpoint, issues related to empirical underidentification would arise should one of the effect indicators (e.g., ENT2, which has a VIF of 5.556) be removed from the analysis. Theoretically, Dweck (1999) contends that each item captures a unique aspect of entity theory. The ENT1 item establishes the belief that intelligence is an entity that cannot be changed. The ENT2 item ties intelligence to self-identity, and the ENT3 item provides differentiation between the concept of learning and the concept of intelligence. Therefore, it was determined that each effect indicator would be retained in the SEM analyses.

Table 10

Univariate Normality and Multicollinearity Diagnostic Statistics

Effect Indicator	Normality Statistics		Collinearity Statistics	
	Skewness	Kurtosis	Tolerance	VIF
ENT1	-.131	-.912**	.219	4.566
ENT2	-.292**	-.758**	.180	5.556
ENT3	-.049	-.891**	.253	3.953
PERF1	.644**	.148	.579	1.727
PERF2	.241*	-.512**	.677	1.477
PERF3	.342**	-.123	.617	1.621
PERF4	.327**	-.474**	.630	1.587
LEARN1	-.648**	.311	.653	1.531
LEARN2	-.293**	-.017	.510	1.961
LEARN3	-.335**	-.211	.678	1.475
LEARN4	-.089	-.332	.618	1.618
AVOID1	.748**	.440	.674	1.484
AVOID2	-.183	-.841**	.480	2.083
AVOID3	-.376**	-.627**	.482	2.075
NEGEFF1	-.542**	-.503**	.650	1.538
NEGEFF2	-1.097**	1.336**	.516	1.938
NEGEFF3	-.976**	1.515**	.568	1.761
NEGEFF4	-.218*	-.538**	.606	1.650
NEGEFF5	-.335**	-.139	.626	1.597
POSEFF1	-.219*	-.394*	.658	1.520
POSEFF2	-.837**	.156	.745	1.342
POSEFF3	-1.088**	1.250**	.571	1.751
POSEFF4	-.448**	-.131	.626	1.597
HELPLES1	-.273*	-.891**	.560	1.786
HELPLES2	.324**	-.187	.787	1.271
HELPLES3	-.029	-.426*	.524	1.908
HELPLES4	-.303**	-.511**	.666	1.502
EFFORT1	-1.671**	4.462**	.621	1.610
EFFORT2	-1.147**	2.256**	.657	1.522
POSSTAT1	-1.643**	5.056**	.273	3.663
POSSTAT2	-1.585**	4.457**	.308	3.247
NEGSTAT1	-1.571**	3.748**	.596	1.678
NEGSTAT2	-.752**	.257**	.565	1.770
SC	-.541**	.307	.653	1.531
SE15	-2.733**	8.685**	.551	1.815
SE610	-.500**	-.516**	.514	1.946
EOCG	-.798**	.493	.914	1.094

Note. **p* < .05; ***p* <.01. Codebook for measured variable mnemonics provided in Appendix E.

Covariance and asymptotic covariance matrices. Following the recommendations of Schumacker and Lomax (2010) and Finney and DiSteffano (2013), a covariance matrix and asymptotic covariance matrix, rather than a correlation matrix, were generated and served as the input for all SEM analyses. Schumacker and Lomax cite Boomsma (1983) who found that use of a correlation matrix can lead to imprecise parameter estimates and standard errors in SEM. Incorrect parameter estimates can, in turn, lead to an incorrect interpretation of the model. Furthermore, the nonnormality of the data is best estimated using the S-B scaled-χ^2 methodology that is based on full-information maximum likelihood (FIML) yet requires use of the asymptotic covariance matrix. The covariance matrix for all measured indicators analyzed in this study is provided in Table 11.

Outliers and Missing Data

Each item was examined using SPSS22 (IBM Corp., 2013) for possible outliers that would distort the goodness-of-fit for each model. Outliers were identified through use of the modified Thompson's τ, comparing the absolute value of deviation for each response from the sample mean and was compared to a critical value based on the number of data points in the sample (Anbarasi, Ghaayathri, Kamaleswari, & Abirami, 2011). If the data point for any item was greater than τ-critical, listwise-deletion was employed and the respondent was removed from the dataset. In total, five cases were removed from the dataset using the modified Thompson's τ method of outlier identification including four SE610 outliers and one SC outlier. Four additional respondents were removed from the analysis as they failed to complete the course in which they were sampled; these listwise deletions resulted in the final sample size of 501

Table 11

Sample Data Covariance Matrix

Variable	ENT1	ENT2	ENT3	PERF1	PERF2	PERF3
ENT1	1.805					
ENT2	1.467	1.648				
ENT3	1.405	1.412	1.760			
PERF1	0.400	0.365	0.344	1.274		
PERF2	0.296	0.265	0.291	0.507	1.349	
PERF3	0.192	0.173	0.168	0.553	0.380	1.096
PERF3	0.349	0.312	0.320	0.479	0.330	0.476
LEARN1	0.108	0.105	0.142	0.077	-0.077	0.062
LEARN2	0.102	0.146	0.189	0.203	-0.125	0.258
LEARN3	0.286	0.238	0.219	0.318	0.069	0.186
LEARN4	0.284	0.276	0.251	0.346	0.133	0.248
AVOID1	0.106	0.127	0.173	0.408	0.391	0.381
AVOID2	0.261	0.249	0.264	0.386	0.436	0.347
AVOID3	0.269	0.320	0.268	0.400	0.344	0.365
NEGEFF1	0.371	0.228	0.247	0.337	0.216	0.218
NEGEFF2	0.499	0.486	0.435	0.165	0.193	0.146
NEGEFF3	0.432	0.450	0.412	0.170	0.133	0.164
NEGEFF4	0.285	0.351	0.353	0.251	0.175	0.231
NEGEFF5	0.290	0.310	0.273	0.183	0.049	0.214
POSEFF1	0.125	0.154	0.147	0.128	0.001	0.244
POSEFF2	0.057	0.082	0.071	-0.171	-0.126	-0.149
POSEFF3	0.262	0.298	0.218	-0.089	-0.074	-0.034
POSEFF4	0.222	0.219	0.252	0.100	-0.078	0.088
HELPLES1	0.573	0.477	0.462	0.382	0.234	0.258
HELPLES2	-0.028	0.028	-0.023	0.095	0.024	0.131
HELPLES3	0.293	0.240	0.228	0.311	0.204	0.229
HELPLES4	0.163	0.180	0.096	0.170	0.090	0.084
EFFORT1	0.098	0.082	0.068	-0.054	-0.044	-0.015
EFFORT2	0.172	0.175	0.122	-0.055	0.025	0.042
POSSTAT1	0.094	0.113	0.120	-0.056	0.020	0.005
POSSTAT2	0.092	0.125	0.128	-0.046	-0.016	0.021
NEGSTAT1	0.174	0.119	0.145	0.125	0.085	0.125
NEGSTAT2	0.240	0.207	0.183	0.200	-0.013	0.277
EOCG	0.024	-0.007	0.014	-0.026	-0.031	-0.019
SC	-0.025	0.239	-0.757	0.533	-1.025	0.318
SE15	1.649	-0.452	-0.007	2.097	-1.745	2.654
SE610	-7.079	-8.580	-1.724	3.080	-11.519	5.083
GPA	0.010	-0.002	0.009	0.025	0.012	-0.005
SAT	15.373	10.562	7.683	7.684	-8.392	-4.014
CRED	-1.796	-1.079	-1.724	-0.920	-0.524	-0.383

Variable	PERF4	LEARN1	LEARN2	LEARN3	LEARN4	AVOID1
PERF4	1.498					
LEARN1	0.284	1.002				
LEARN2	0.277	0.451	1.004			
LEARN3	0.323	0.299	0.439	1.247		
LEARN4	0.529	0.445	0.463	0.571	1.471	
AVOID1	0.397	0.087	0.124	0.128	0.226	1.216
AVOID2	0.445	0.208	0.146	0.169	0.259	0.608
AVOID3	0.538	0.191	0.274	0.197	0.197	0.518
NEGEFF1	0.331	0.125	0.132	0.171	0.087	0.227
NEGEFF2	0.231	0.099	0.101	0.268	0.156	0.140

NEGEFF3	0.218	0.077	0.141	0.191	0.127	0.076
NEGEFF4	0.190	0.076	0.217	0.120	0.138	0.162
NEGEFF5	0.202	0.076	0.279	0.118	0.162	0.096
POSEFF1	0.378	0.325	0.498	0.388	0.346	0.128
POSEFF2	0.053	0.155	0.079	0.075	0.105	-0.137
POSEFF3	0.028	0.167	0.187	0.194	0.164	-0.017
POSEFF4	0.278	0.358	0.410	0.363	0.405	0.009
HELPLES1	0.314	0.142	0.189	0.217	0.185	0.213
HELPLES2	0.217	0.000	0.145	0.160	0.092	-0.150
HELPLES3	0.294	0.102	0.242	0.211	0.079	0.238
HELPLES4	0.306	0.163	0.197	0.196	0.066	0.138
EFFORT1	0.040	0.160	0.060	0.102	0.092	-0.150
EFFORT2	0.046	0.155	0.058	0.092	0.132	-0.086
POSSTAT1	0.056	0.140	0.102	0.136	0.076	-0.078
POSSTAT2	0.076	0.180	0.128	0.142	0.116	-0.060
NEGSTAT1	0.171	0.106	0.148	0.163	0.055	0.036
NEGSTAT2	0.341	0.209	0.256	0.268	0.230	0.042
EOCG	-0.022	0.044	-0.030	0.032	-0.024	-0.032
SC	2.369	3.253	4.039	2.766	3.118	0.960
SE15	0.522	5.114	5.131	4.441	1.060	1.493
SE610	15.185	18.256	21.375	12.538	14.492	9.867
GPA	0.004	0.013	-0.003	0.011	-0.006	-0.001
SAT	14.457	-9.614	-17.471	2.525	-2.985	-5.642
CRED	-0.246	0.880	1.050	-0.466	-0.110	-0.554

Variable	AVOID2	AVOID3	NEGEFF1	NEGEFF2	NEGEFF3	NEGEFF4
AVOID2	1.751					
AVOID3	1.125	1.720				
NEGEFF1	0.483	0.451	1.700			
NEGEFF2	0.271	0.343	0.591	1.090		
NEGEFF3	0.247	0.321	0.351	0.553	1.021	
NEGEFF4	0.283	0.382	0.493	0.369	0.510	1.361
NEGEFF5	0.155	0.340	0.400	0.306	0.362	0.545
POSEFF1	0.129	0.2262	0.211	0.128	0.167	0.257
POSEFF2	-0.096	0.022	0.039	0.038	0.093	-0.086
POSEFF3	0.034	0.116	0.202	0.348	0.289	0.156
POSEFF4	0.160	0.202	0.253	0.216	0.240	0.210
HELPLES1	0.365	0.482	0.605	0.480	0.401	0.562
HELPLES2	0.023	0.118	0.094	0.063	0.086	0.112
HELPLES3	0.251	0.319	0.372	0.332	0.290	0.325
HELPLES4	0.272	0.250	0.188	0.188	0.160	0.092
EFFORT1	-0.002	-0.027	0.028	0.099	0.128	0.030
EFFORT2	0.013	0.008	0.069	0.169	0.092	0.031
POSSTAT1	0.045	0.068	0.082	0.156	0.163	0.090
POSSTAT2	0.071	0.072	0.122	0.154	0.155	0.100
NEGSTAT1	0.169	0.205	0.263	0.268	0.232	0.186
NEGSTAT2	0.218	0.260	0.305	0.252	0.364	0.276
EOCG	-0.012	0.036	-0.011	0.037	0.053	-0.007
SC	1.557	2.287	1.571	1.522	1.383	2.819
SE15	3.762	7.097	8.053	7.821	5.736	7.039
SE610	17.893	18.494	23.338	12.082	7.135	22.501
GPA	0.022	0.005	-0.003	-0.023	-0.010	0.035
SAT	-2.190	2.545	-10.842	-5.979	-0.386	0.113
CRED	0.348	-0.208	1.046	0.046	-0.451	0.746

Variable	NEGEFF5	POSEFF1	POSEFF2	POSEFF3	POSEFF4	HELPLES1
NEGEFF5	0.979					
POSEFF1	0.201	1.330				

POSEFF2	0.014	0.159	1.514			
POSEFF3	0.176	0.214	0.467	0.942		
POSEFF4	0.230	0.525	0.301	0.501	1.500	
HELPLES1	0.372	0.147	-0.009	0.251	0.196	1.907
HELPLES2	0.103	0.081	0.000	0.015	0.162	0.166
HELPLES3	0.224	0.193	0.034	0.105	0.114	0.840
HELPLES4	0.140	0.128	0.145	0.031	0.061	0.214
EFFORT1	0.094	0.095	0.201	0.159	0.194	-0.103
EFFORT2	0.100	0.117	0.189	0.162	0.207	0.059
POSSTAT1	0.103	0.201	0.232	0.212	0.260	0.014
POSSTAT2	0.107	0.233	0.246	0.202	0.258	0.014
NEGSTAT1	0.266	0.186	0.156	0.136	0.231	0.226
NEGSTAT2	0.312	0.224	0.181	0.165	0.387	0.375
EOCG	-0.046	0.046	0.132	0.062	0.086	-0.020
SC	2.084	2.806	0.632	0.977	3.722	2.831
SE15	5.611	6.043	1.324	0.991	4.315	7.902
SE610	11.669	25.399	-0.912	6.362	16.347	23.274
GPA	-0.016	0.012	-0.024	-0.020	0.015	-0.003
SAT	-2.465	-9.080	0.284	-1.142	-0.191	-7.754
CRED	-0.198	0.452	-0.390	0.054	0.116	0.202

Variable	HELPLES2	HELPLES3	HELPLES4	EFFORT1	EFFORT2	POSSTAT1
HELPLES2	1.230					
HELPLES3	0.343	1.261				
HELPLES4	0.309	0.517	1.461			
EFFORT1	0.140	-0.025	-0.005	0.723		
EFFORT2	0.058	0.006	-0.059	0.302	0.746	
POSSTAT1	0.051	0.023	0.067	0.315	0.291	0.519
POSSTAT2	0.101	0.029	0.115	0.285	0.249	0.427
NEGSTAT1	0.189	0.230	0.273	0.155	0.187	0.276
NEGSTAT2	0.324	0.476	0.558	0.140	0.210	0.156
EOCG	0.034	0.013	0.028	0.088	0.106	0.156
SC	0.441	2.828	1.772	0.075	0.499	1.158
SE15	3.729	7.705	5.658	3.815	3.055	4.832
SE610	8.823	19.545	5.260	4.331	1.888	8.823
GPA	-0.013	0.001	-0.005	-0.011	0.001	-0.008
SAT	6.381	-2.034	-0.376	-6.579	-7.987	-7.212
CRED	-0.055	0.283	-0.001	0.494	0.319	0.300

Variable	POSSSTAT2	NEGSTAT1	NEGSTAT2	EOCG	SC	SE15
POSSTAT2	0.539					
NEGSTAT1	0.282	0.797				
NEGSTAT2	0.190	0.440	1.356			
EOCG	0.147	0.058	0.052	0.512		
SC	0.996	1.444	3.512	-0.646	154.173	
SE15	3.840	6.753	8.197	-1.332	156.573	1638.056
SE610	4.745	3.403	11.629	-4.898	498.047	2597.376
GPA	-0.005	-0.005	0.012	0.020	-0.082	0.338
SAT	-2.742	0.083	10.988	23.434	-269.561	-1051.821
CRED	0.120	0.192	-0.840	-1.916	28.848	65.609

Variable	SE610	GPA	SAT	CRED
SE610	11309.148			
GPA	-0.291	0.050		
SAT	-3429.664	0.898	16267.600	
CRED	291.482	-0.141	-576.602	95.257

Note. Codebook for measured variable mnemonics provided in Appendix E.

respondents. When calculating descriptive statistics for each item, missing data was handled with pairwise deletion. Pairwise deletion excludes cases in descriptive measures only if they are missing data required for the analysis rather than excluding them entirely from the analysis (Pallant, 2010). For the confirmatory factor and latent variable path analyses incorporated in SEM, full-information maximum likelihood (FIML) estimation was used to account for missing data during parameter estimation. FIML estimation allows all respondents to contribute to those parameter estimates for which their available data is able to inform (Mueller & Hancock, 2010). While FIML typically assumes a univariate normality of distribution in the data, the S-B scaled-χ^2 methodology corrects the mean and standard errors of the estimates to alleviate the bias presented by the nonnormality of the sample data (Finney & DiSteffano, 2013).

Recoding of Select Variables

As described earlier, five sets of items were reverse coded so that higher values consistently demonstrated favorable conditions: (1) mastery-oriented goal items; (2) positive valence effort belief items; (3) effort-oriented failure attribution items; (4) mastery-oriented strategy items; and (5) negative valence self-concept items.

Latent Factors and Measured Effect Indicators

This study sought to assess nested models initially composed of two exogenous latent factors, five endogenous latent factors, and 37 measured indicator variables. The latent variables underlying the stage-one validation model proposed by Dweck (1999) included implicit theories of intelligence (or mindsets), goal orientations, effort beliefs, failure attribution, and achievement strategies. Implicit theories of intelligence were identified by three entity-oriented observed indicators (ENT1-ENT3). Goal orientation was initially identified by 11 measured variables parceled into three categories: performance goal orientation (PERF1 – PERF4), learning goal orientation (LEARN1 – LEARN4), and performance-avoidant goal orientation (AVOID1 – AVOID3). Effort beliefs were initially identified by nine measured variables, five negative-valence effort items (NEGEFF1 – NEGEFF5) and four positive-valence effort items (EFFORT1 – EFFORT4). Failure attribution had six observed indicators, four that attributed helplessness to failure (HELPLES1 – HELPLES4) and two that attributed lack of effort to failure (EFFORT1 and EFFORT2). Finally, achievement strategies had four indicators measuring one's use of positive (POSSTAT1 and POSSTAT2) or negative (NEGSTAT1 and NEGSTAT2) academic strategies after experiencing failure. The endogenous outcome criterion for the model was student academic achievement, operationalized as the end-of-course grade earned in the sampling frame course for the Spring, 2014 semester (EOCG). The stage two alternative hypothesis model appended an additional latent factor: academic self-perception. Academic self-perception was composed of three measured indicators. The first indicator was the summed score across the domain-specific self-concept items (SC). The second indicator was the summed score of the first five self-efficacy items (SE15), while the third indicator was the summed score of items 6 through 10 on the self-efficacy scale (SE610). See appendix E for a description of each measured variable.

Statistical Analysis

In light of the *a priori* specified hypotheses concerning the direct and indirect effects of mindsets and academic motivation on academic achievement outcomes, structural equation modeling (SEM) served as the appropriate method for analysis for this study. SEM encompasses two forms of statistical analysis that evaluate the grounds for making causal inferences among measured and latent variables: *confirmatory factor analysis* (CFA) and *latent variable path analysis* (LVPA; Mueller & Hancock, 2010). CFA and LVPA are analysis techniques used in conjunction with a hypothesized model to compare an estimate of a population covariance matrix with an observed covariance matrix (Schrieber et al., 2006). CFA is utilized to validate (or confirm) the use of observed variables (or indicators) to identify latent factors (i.e., an unobservable factor that is hypothesized to have a causal bearing on one or more measured variables) (Mueller & Hancock, 2010). LVPA evaluates hypothesized causal models composed of latent factors (identified by indicator variables) and related parameters in order to describe the direct and indirect effects between these constructs. Typically, CFA is conducted in association with LVPA to validate the latent constructs on which the hypothesized conceptual model is formed. While some have suggested that SEM is appropriate for exploratory purposes (Ullman, 2001), Mueller and Hancock (2010) have argued that SEM is best used to compare correlational data with causal theories specified *a priori*. SEM is useful not only for testing direct and indirect effects of observed and latent variables, but it also provides a visual description of the relationship between the variables (Schumacker & Lomax, 2010). SEM requires a theoretical basis for model specification, identified model equations, complete data, and both continuously and normally distributed endogenous variables (Hancock & Mueller, 2006).

Confirmatory Factor Analysis

In order to analytically assess the validity of Dweck's (1999) specified model according to a post-secondary population or compare the fit of the nested models, the composition of the latent factors that comprise the nested models needed to first be evaluated. CFA was conducted for each of the latent constructs in both stage-one and stage-two models. CFA serves as a method for assessing the validity and reliability of a construct while accounting for the measurement error associated with the data collection method (Schumacker & Lomax, 2010). Using CFA, the observed items from the data set represent effect indicators upon which their corresponding latent factors are regressed. In addition, error terms are calculated for each associated indicator variable. For the present study, CFA served to verify the appropriateness of using particular variables as indicators for their corresponding latent factors while determining the significance of the association between the measured variable and latent factor. To test the reliability of the construct, Coefficient *H* (Maximal Reliability) was measured using the standardized loadings for each indicator variable on the latent factor. Coefficient *H* assesses the stability of a construct as reflected in the sample data by the measured indicators; Coefficient *H* is not affected by a loading's sign nor does it decrease with additional indicators (Hancock & Mueller, 2001). Reliable measures were indicated by having a high Coefficient *H* approaching 1.00 (Nunnally & Bernstein, 1994; Hair, Anderson, Tatham, & Black, 1998).

To determine the validity of using the measured variables as indicators of the latent factors, several indices were assessed. First, the root-mean-square error of approximation (RMSEA) was measured to assess the parsimony of the data (i.e., whether the appropriate number of estimated parameters were used to explain the data variance; Schumacker & Lomax, 2010). R^2 values indicating the total variance of the latent factor explained by the effect indicators were also assessed for significance. Standardized residual covariance matrices were examined to determine whether the observed covariance in the data was sufficiently reproduced by the implied latent construct model. Schumacker and Lomax (2010) suggest comparing the residual values to determine whether the covariance between particular variables can be explained through related parameters or whether the utility of the variable is adequate. Finally, LISREL 9.1 (Jöreskog & Sorböm, 2013) provides a modification index for each parameter that, if theoretically and conceptually sound, can be specified in order to improve the factor. Changes to factor models as a result of examining the standardized residual covariance matrix or modification indices were grounded in theory.

Model specification. For each of the latent variables, a model was specified indicating the hypothesized directional relationships between the latent factor and the effect indicators (indicated by single-headed arrows). Observed variables were displayed using squares, while latent factors were displayed using circles. Double-headed arrows signified correlations or covariances. In each model, a factor loading of 1 was fixed for the regression of a single effect indicator. This *reference variable* served two functions: (a) it provided a unit of measurement for the latent variable; and (b) all other effect indicators were interpreted in relation to the reference variable's unit of measurement (Schumacker & Lomax, 2010). Each effect indicator was accompanied by an error term and error variance.

Three effect indicators were initially associated with the implicit theories of intelligence construct (ITI). The specified measurement model for ITI is depicted in Figure 5. Error terms were initially assumed to be uncorrelated. The reference variable assigned for this factor was ENT1, whose unit of measurement is according to a 6-point Likert-type scale.

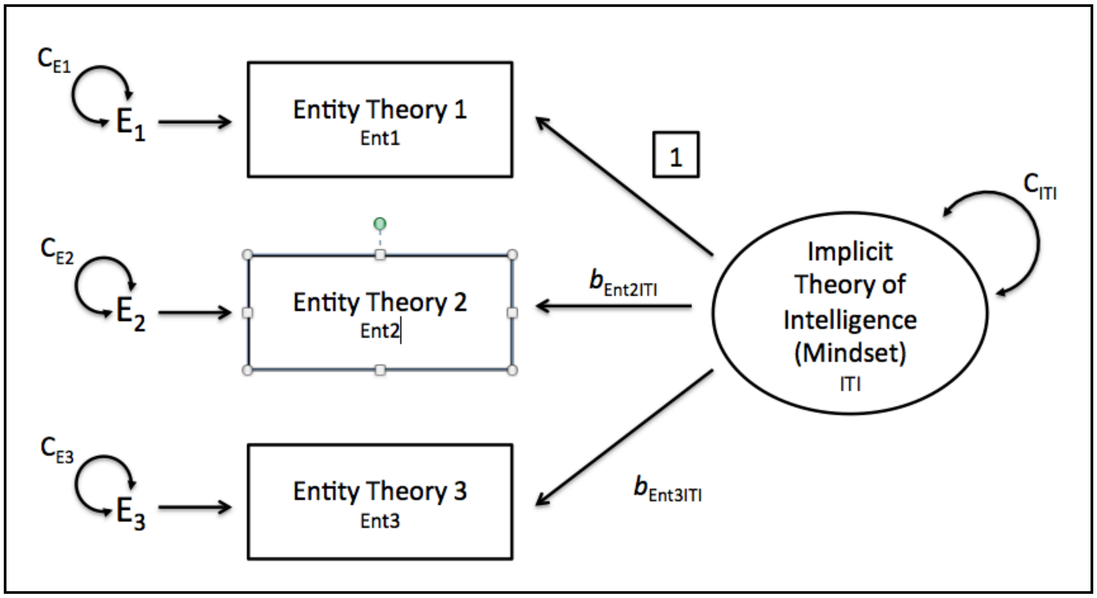

Figure 5. Initial Implicit Theory of Intelligence (ITI) confirmatory factor model.

The initial goal orientation (GOAL) construct was composed of 11 indicator variables couched in three parceled indices: performance orientation, mastery orientation, and performance avoidance orientation. The specified measurement model for goal orientation is depicted in Figure 6. The reference variable for the GOAL constructs was PERF1, whose unit of measure was a 6-point Likert-type scale. Measures for each variable used a 6-point Likert-type scale for data collection. Once again, error terms were initially assumed to be uncorrelated.

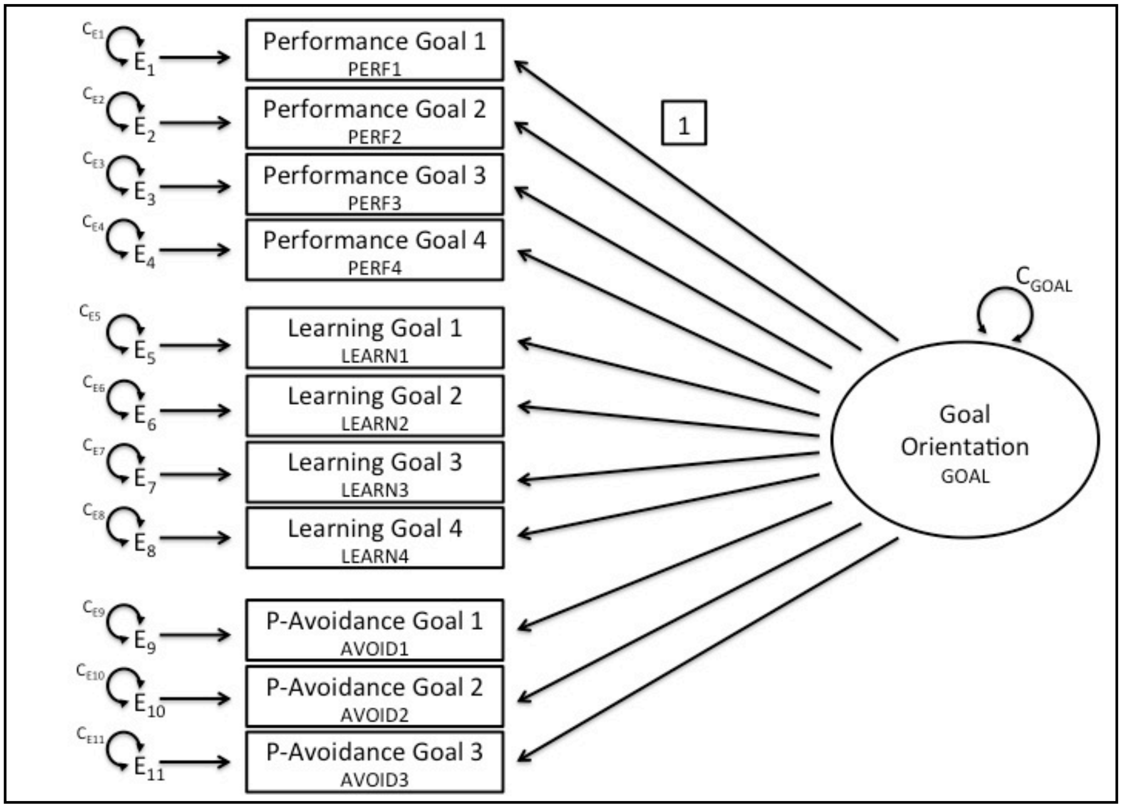

Figure 6. Initial Goal Orientation (GOAL) confirmatory factor model. Individual paths between the GOAL latent factor and effect indicators not specified due to imaging constraints (path from GOAL to PERF2 = $b_{\mathrm{PERF2GOAL}}$, path from GOAL to PERF3 = $b_{\mathrm{PERF3GOAL}}$, etc.).

Nine observed variables served as indicators for the effort beliefs (EFFORT) subscale couched in two parceled indices: negative valence effort beliefs (i.e., effort is futile) and positive valence effort beliefs (i.e., effort is useful). The specified measurement model for EFFORT is depicted in Figure 7. Error terms were initially assumed to be uncorrelated, and NEGEFF1 served as the reference variable for the construct. NEGEFF1 was measured according to a 6-point Likert-type scale.

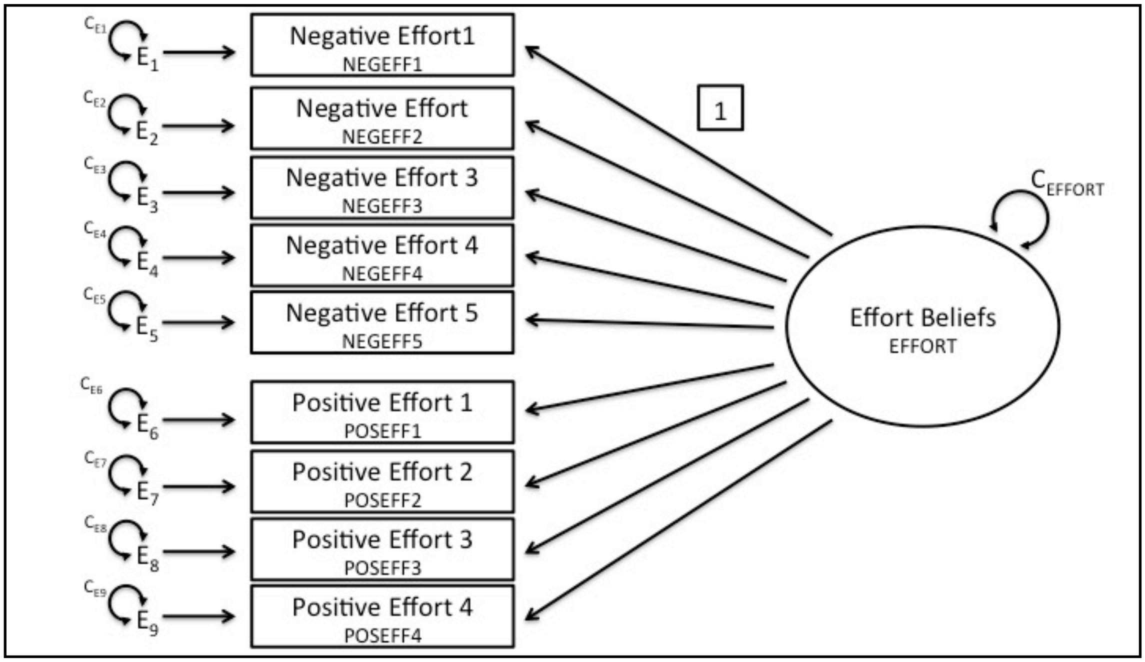

Figure 7. Initial Effort Beliefs (EFFORT) confirmatory factor model. Individual paths between the EFFORT latent factor and effect indicators not specified due to imaging constraints (path from EFFORT to NEGEFF1 = $b_{\text{NEGEFF1EFFORT}}$, path from EFFOFT to NEGEFF2 = $b_{\text{NEGEFF2EFFORT}}$, etc.).

Six measured variables served as indicators for the initial failure attribution (FAIL) latent construct: four helpless-oriented measures and two effort-oriented measures. The specified measurement model for failure attribution is depicted in Figure 8. Error terms were again assumed to be uncorrelated in the initial model. The reference variable assigned for this factor was EFFORT1 measured on a 6-point Likert-type scale.

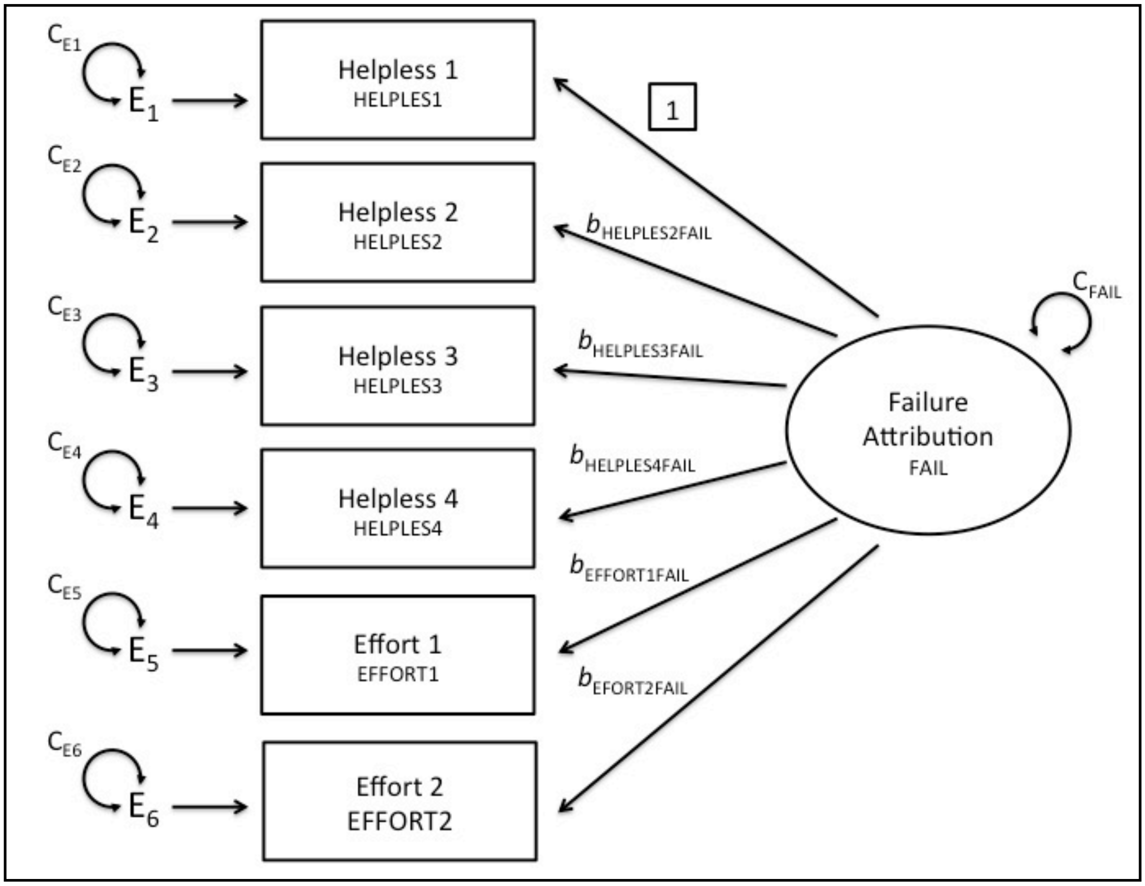

Figure 8. Initial Failure Attribution (FAIL) confirmatory factor model.

The initial achievement strategies (STRAT) construct incorporated four observed variables: two negative strategy indicators and two positive strategy indicators. The specified measurement model for STRAT is depicted in Figure 9. All error terms were initially assumed to be uncorrelated. POSSTAT1 served as referent for the measured scale, a 6-point Likert-type scale.

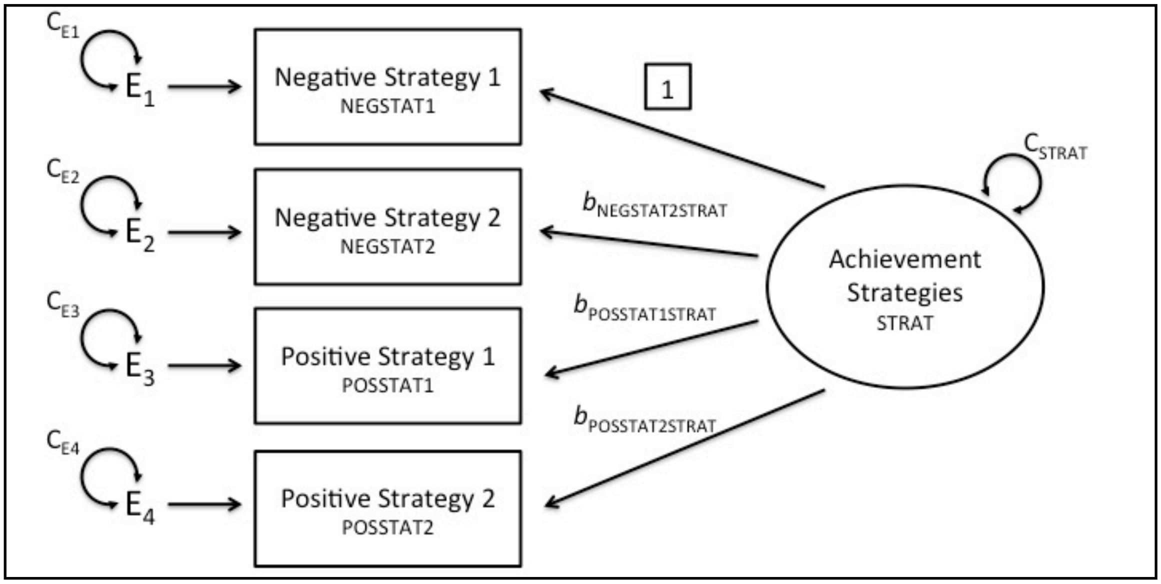

Figure 9. Initial Achievement Strategies (STRAT) confirmatory factor model.

A final model specifying the effect indicators for academic self-perception (ASP) is depicted in Figure 10. The construct was measured using two scales – Marsh and O'Neill's (1984) SDQ III and Bandura's (2006) *Problem Solving Self-efficacy Scale.* As originally conceptualized, summed scores from the 10 SDQ III items and the 10 items from the *Problem Solving Self-efficacy Scale* were to be used as effect indicators for the ASP factor. However, with only two indicators, the construct would be underidentified and would not allow accurate estimation of each parameter (Mueller & Hancock, 2010). To mitigate this issue, the 10 items from the *Problem Solving Self-efficacy Scale* were analyzed to understand if particular sub-components could be identified among the 10 items. Using SPSS 21, the 10 items were subjected to principle components analysis (PCA). The suitability for PCA was first assessed according to statistical measures provided by SPSS: Bartlett's test of sphericity (Bartlett, 1954) and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Kaiser 1974). Bartlett's test of sphericity was significant, p <.05 while the KMO index measured .839, which indicated acceptable levels for factor analysis. Two factors were then extracted according to PCA with oblimin rotation (Pallant, 2010). The pattern matrix revealed the rotated items loading on two factors in distinct patterns, where items 6 through 10 loaded above .6 on the first component and explained 62.8 percent of the variance, while items 1 through 5 loaded above .5 on the second component, explaining 20.7 percent of the variance (see Table 12 for pattern and structure matrices). A screeplot of eigenvalues above 1.0 revealed a clear break between the second and third components, confirming the extraction of two components from the ten items. In total, the two-component solution explained 83.5 percent of the variance. The interpretation of the components is consistent with previous research concerning academic rigor and self-efficacy, whereby items 6-10 that indicated high rigor (e.g., “I am certain can solve 100% of the academic problems in my [science] class on the next exam) loaded on one component where items 1-5 indicating low rigor (e.g., “I am certain I can solve 10% of the academic problems in my [math] class on the next exam) loaded on a separate component. There was a moderate correlation between the two factors, r = .351. The Cronbach’s alpha reliability coefficients were .932 and .887 for the SE610 and SE15 scales respectively.

Having divided the self-efficacy indicators among two components, the analysis of the ASP construct was just-identified by three factors: the summed score of the self-concept items (SC), the summed scores of the first five self-efficacy items (SE15), and the summed scores of the last five self-efficacy items (SC610). Error terms were initially assumed to be uncorrelated, and SC served as the reference variable with a possible scale ranging from 0 to 80.

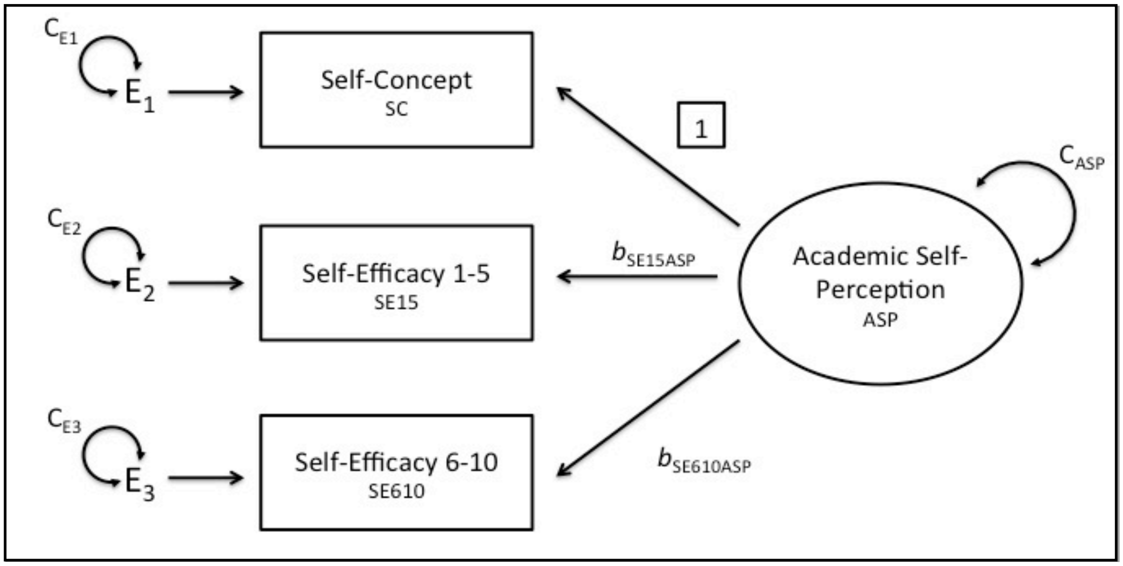

Figure 10. Initial Academic Self-perception (ASP) confirmatory factor model.

Table 12

Pattern and Structure Matrix for PCA with Oblimin Rotation of Two Factor Solution of Self-efficacy items.

Item	Pattern Coefficients		Structure Coefficients		Communalities
	Component 1	Component 2	Component 1	Component 2	
SE9	**.964**	-.090	**.951**	.431	.876
SE8	**.912**	.111	**.932**	.248	.916
SE10	**.891**	-.222	**.896**	.555	.704
SE7	**.800**	.274	**.830**	.663	.869
SE6	**.682**	.424	**.813**	.091	.847
SE2	-.054	**.960**	.282	**.941**	.887
SE3	.094	**.905**	.412	**.938**	.888
SE1	-.179	**.882**	.564	**.883**	.669
SE4	.289	**.781**	.131	**.819**	.852
SE5	.517	**.577**	.720	**.759**	.811

Note. Major loadings for each item are bolded.

Model estimation. Once specified, each measurement model was estimated using robust maximum likelihood (ML) in LISREL, version 9.1 (Jöreskog & Sorböm, 2013) and assessed according to the S-B scaled-χ^2 scaling method (a detailed explanation of the robust ML estimation technique and the S-B scaled-χ^2 method is discussed later in this chapter). Coefficient *H* was reported to assessed the reliability of the construct. Covariance and standardized residual covariance matrices were reported along with standardized estimates and error variances for each effect indicator.

Model testing and modification. Select fit-indices were also reported to demonstrate the goodness-of-fit for each specified model onto the sample data. Recommended fit indices (Mueller & Hancock, 2010) reported in the analysis included the standardized root mean square residual (SRMR; absolute index), the root mean square error of approximation (RMSEA; parsimonious index), and the comparative fit index (CFI; incremental index). While the Satorra-Bentler (1988) Scaled-$\chi^2$was also reported, it was ignored if other fit indices were met given the tendency for the χ^2 test to detect trivial deviations in the data (Mueller & Hancock, 2010; Schumacker & Lomax, 2010). If the models did not meet the threshold for each goodness-of-fit criterion, the standardized residual matrices were reviewed to assess if any observed covariances were greater than $t = 2.58$, $\alpha = .05$, indicating possible misspecification. According to Schumacker & Lomax (2010), standardized residuals (SR) emulate *z* scores, whereby the SR indicates whether the relationship between the effect indicator and the factors is well accounted for by the model. Misspecified measurement models were also modified according to recommendations made by LISREL (if the recommendation was theoretically sound). Modifications were specified, new models were estimated, and goodness-of-fit tests were once again run to provide final measurement models to inform the LVPA.

Statistical Procedures for Latent Variable Path Analysis

Given both the *a priori* analysis by Blackwell et al. (2007) to test the relationships in Dweck's (1999) model of motivation and achievement, and the methodological considerations for analyzing hypothesized causal relationships among observed and latent variables, the present study employed LPVA to address the overarching research questions: (a) Do implicit theories of intelligence (or mindsets) play a significant role in academic motivation and achievement in introductory STEM courses at the collegiate level; and (b) does the addition of an academic self-perception factor (a higher-order factor encompassing domain-specific measures of self-concept and self-efficacy) add to the explanatory power of Dweck's (1999) model, using a sample of first- and second-year college students enrolled in STEM courses? LPVA serves to test both direct effects, such as the relationship between mindsets and effort beliefs, and indirect ones, like the effect of mindsets on achievement strategies that is mediated through effort beliefs or goal orientation (Schumacker & Lomax, 2010). In addition, LPVA permits an analysis of the direct effects (which represent causal effects of exogenous variables on endogenous variables), and indirect effects (i.e., mediating effects) to be modeled together (Schumacker & Lomax, 2010).

Two-phase modeling approach. Following the recommendation of Mueller and Hancock (2010), analysis of all hypothesized models followed a two-phase modeling approach. In the first phase – the *measurement model phase* – the latent constructs and the achievement outcome indicator for each model was allowed to freely covary. Parameters were then estimated for the fully covaried models, and tests of model fitness were conducted to determine if the data sufficiently fit the factors simultaneously. If satisfactory model fit was achieved, the second phase of modeling commenced. The second phase (i.e., *structural modeling phase*) began by specifying the *a priori* hypothesized relationships between the latent factors for each model. Models were then identified, estimated, and tested for goodness-of-fit.

Model specification. To determine whether mindsets affect the motivation and academic achievement of first- and second- year college students enrolled in STEM courses according to the relationships proposed by Dweck (1999), Dweck's conceptual model was initially specified. One exogenous variable, implicit theories of intelligence (ITI), was regressed onto two endogenous factors, goal orientation and effort beliefs. Effort beliefs was regressed on to the failure attribution endogenous factor, while goal orientation, effort beliefs, and failure attribution were all regressed on the endogenous achievement strategies factor. Finally, the achievement strategies factor was regressed onto an achievement outcomes measure, the students' end of course grade for the class in which they were enrolled for participation in this course. Figure 11 depicts the initial specification for the stage-one model.

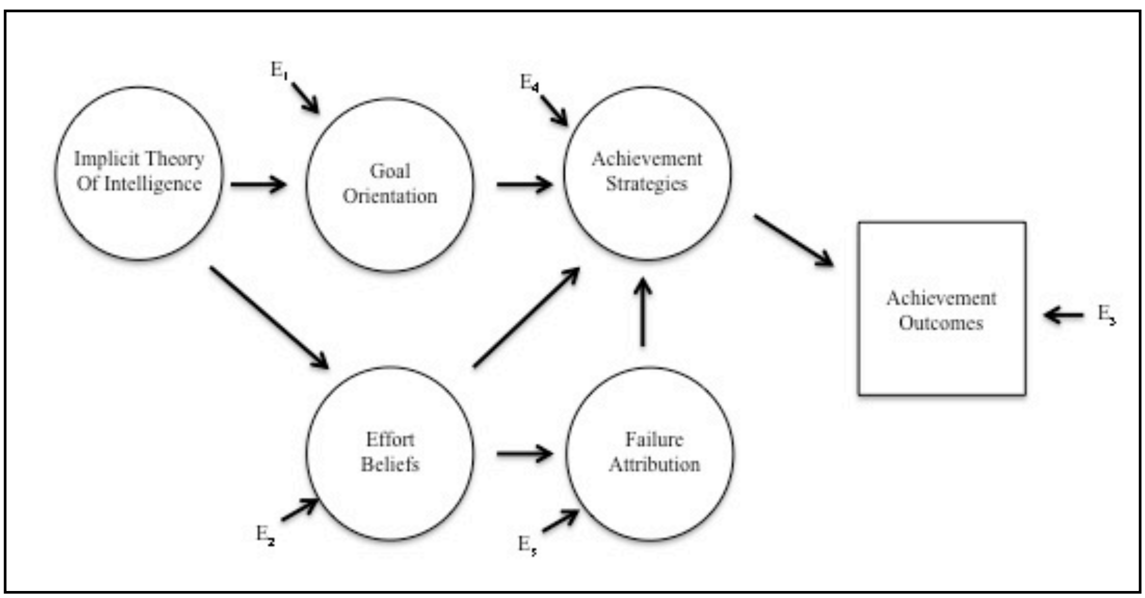

Figure 11. Initial stage-one structural model with hypothesized relationships among latent factors and error terms specified.

The proposed structural model equation for the initial stage-one model was interpreted as follows:

Achievement Outcomes = f (achievement strategies) + E_5, and

Achievement strategies = f (goal orientation, effort beliefs, failure attribution) + E_4, and

Failure attribution = f (effort beliefs) +E_3, and

Effort beliefs = f (implicit theories of intelligence) + E_2, and

Goal orientation = f (implicit theories of intelligence) + E_1,

where E_i was the error term (i.e., the vector of all other factors that were not accounted for in the model).

To determine whether accounting for students' academic self-perceptions would add to the explanatory power of Dweck's theory, academic self-perception was regressed onto goal orientation and achievement strategies in the stage-two structural model. Academic self-perception was regressed onto the final achievement outcome measure as well. Academic self-perception was conceptualized as an exogenous factor that served a discrete role in this model of intrapersonal motivation; therefore, academic self-perception and implicit theories of intelligence were not covaried in the structural model. Figure 12 depicts the stage-two structural model.

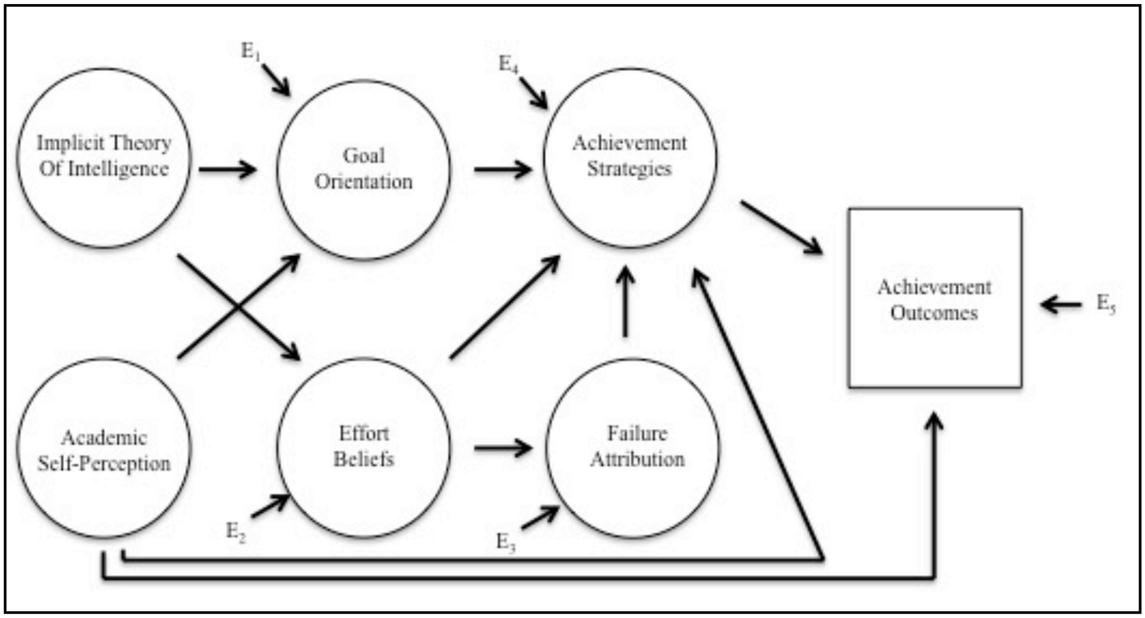

Figure 12. Initial stage-two structural model with hypothesized relationships among latent factors and error terms specified.

The proposed structural model equation for the initial stage-two alternative hypothesis model was interpreted as follows:

Achievement outcomes = f (achievement strategies, academic self-perception) + E_5, and

Achievement strategies = f (goal orientation, effort beliefs, failure attribution, academic self-perception) + E_4, and

Failure attribution = f (effort beliefs) +E_3, and

Effort beliefs = f (implicit theories of intelligence) + E_2, and

Goal orientation = f (implicit theories of intelligence, and academic self-perception) +E_1, where E_i was the error term (i.e., the vector of all other factors that were not accounted for in the model).

Finally, a stage-three modified model of mindsets and achievement motivation at the post-secondary level was constructed as part of a *post hoc* analysis to determine whether any tenable explanation of mindsets and motivation could be modeled given the sample data. The stage-three model specifications were developed in consideration of both the literature regarding the spurious nature of goal orientation and the stage-one and stage-two results. The stage-three model is a nested model that specified all relationships in the stage-one model other than those associated with goal orientation. The proposed structural equation for the for the initial stage-three modified model of mindsets and achievement motivation at the post-secondary level was interpreted as follows:

Achievement outcomes = f (achievement strategies, academic self-perception) + E_4, and

Achievement strategies = f (, effort beliefs, failure attribution) + E_3, and

Failure attribution = f (effort beliefs) +E_2, and

Effort beliefs = f (implicit theories of intelligence) + E_1,

where E_i was the error term (i.e., the vector of all other factors that were not accounted for in the model).

Model identification and estimation. Before parameters for either of the measurement or structural models could be estimated, the theoretical models had to be analyzed to understand if a unique set of parameter estimates could be calculated or *identified* from the given sample covariance matrix (Schumacker & Lomax, 2010). Two conditions for identification were analyzed. The first condition for proper identification requires that the number of free parameters to be estimated is less than the number of real data points in the sample covariance matrix. The second condition requires that the theoretical relationships in the model do not create empirical underidentification through either *indeterminacy* or *nonrecursivity*. Indeterminacy may be present when the variance of the latent variables does not match the loadings of the observed variables, while nonrecursivity occurs when a feedback loop is created when a latent variable feeds back onto itself through specified relationships (Schumacker & Lomax, 2010). Indeterminacy is solved by fixing the loading of one variable (i.e., the indicator variable) to 1 for each latent construct. Nonrecursivity must be solved during specification. All specified models in both stage one and stage two were recursive (i.e., unidirectional).

Once the specified models were considered identified, the models were then estimated, whereby a unique regression equation was assigned to each relationship between the exogenous (independent) or endogenous (dependent) factors. Parameters were then estimated using the robust ML estimation technique in LISREL 9.1 (Jöreskog & Sorböm, 2013), whereby the discrepancy between the observed covariance in the sample matrix and the implied covariance in the model is minimized (Finney & DiStefano, 2013). ML was selected as an estimation technique for a number of reasons. First, ML is employed more often for LVPA than other methods due to its unbiased, efficient, scale invariant, scale free, and normally distributed estimates when compared to generalized least squares (GLS) and asymptotically distribution free techniques (Schumacker & Lomax, 2010). Second, ML is robust against violations of multivariate assumptions among latent factors (Schumacker & Lomax, 2010). However, ML does assume that univariate normality does exist among observed variables. When presented with nonnormal data, the ML χ^2 estimate can be biased upward or downward based on the distribution of the data, even when a model is correctly specified (Finney & DiStefano, 2013). To account for the observed nonnormality in the sample data (see Table 10), this study employed the Satorra-Bentler (S-B; 1988) scaling method to adjust the ML χ^2 estimate to better reflect the nonnormal distribution of the data. The S-B scaling method adjusts the mean of the ML χ^2 statistic to better reflect the distributional characteristics of the sample data (Finney & DiStefano, 2013). Standard errors are also corrected through the S-B method to approximate standard errors that would have been found in normally distributed data (Finney & DiStefano). Goodness-of-fit indices are also adjusted to the S-B scaling method accordingly. In their review of empirical tests comparing the use of S-B scaled fit indices to unadjusted fit indices, Finney and DiStefano suggest the scaled fit-indices approximate or, in some instances, outperform unadjusted indices.

Model testing. Following the recommendation of Mueller and Hancock (2010), four goodness-of-fit indices were calculated to evaluate how the observed data fit the validation and hypothesized models. To assess the absolute fit (i.e., overall fit) of each model, the SRMR index was measured. The SRMR compared the discrepancy between the covariance in the sample data and the model covariance. The SRMR ranges from 0 to 1, with a value below .08 indicating good overall model fit (Mueller & Hancock, 2010). A comparison of the predicted model relative to the null hypothesis model (incremental fit) was tested using the CFI. The CFI measures how well the theoretical model improves the noncentrality of the distribution from the null distribution (Schumacker & Lomax, 2010). The CFI ranges from 0 to 1, with a value greater than .95 indicating good fit (Mueller & Hancock, 2010). To test the parsimony of the model, the RMSEA was used. The RMSEA assessed the discrepancy between the hypothesized model with optimal parameter estimates and the sample covariance matrix. The RMSEA also ranges from 0 to 1, with a value between .08 and .05 indicating good parsimony in the model, or a value below .05 indicating excellent parsimony (MacCallum et al., 1996). The RMSEA also computes a confidence interval, whereby if the interval exceeds .05 or .08 on both limits, excellent or good fit is rejected accordingly (Hancock, 2014). Finally, the Satorra-Bentler (1988) Scaled-χ^2 was measured to indicate whether the observed covariance in the sample data is significantly different than the implied covariance in the model. A non-significant scaled-χ^2 would suggest that the implied model demonstrates proper fit according to the data. While the χ^2 estimate is commonly reported in SEM analyses, the index is prone to detect trivial deviations with large sample sizes above 200 (Mueller & Hancock, 2010; Schumacker & Lomax, 2010) and is only reported for ancillary purposes. Model fit indices were calculated using LISREL 9.1(Jöreskog & Sorböm, 2013).

Model Comparisons

When it was appropriate to compare specified models, nested models were compared using the S-B scaled difference test (or likelihood ratio test). This comparison served to indicate whether the implied covariance in Dweck's (1999) model better fit the sample data than the nested hypothetical model including academic self-perception. The S-B scaled difference test was calculated in two steps according to the suggestions of Bryant & Satorra (2012). First, the scaling correction factor (*c*) for the S-B scaled -χ^2 test statistic was determined by dividing the normal theory weighted least-squares (NTWLS) χ^2 statistic by the S-B scaled-χ^2 statistic. The formula for this equation is provided:

$$c = \chi^2_{\text{NTWLS}} / \chi^2_{\text{SB}}$$

The S-B scaled difference χ^2 test statistic was then calculated by subtracting the χ^2_{NTWLS} of Dweck's model from the χ^2_{NTWLS} of the nested model, then dividing the difference by the scaling correction factor. The formula for this calculation is provided:

$$\text{S-B scaled difference } \chi^2 = (\chi^2_{\text{NTWLS}} \text{ for } M_0 - \chi^2_{\text{NTWLS}} \text{ for } M_1)/c$$

Results calculated from the S-B scaled difference test were assessed according to the calculated effect size and power provided by the sample size. The significance of the effect size was assessed according to the difference between the degrees of freedom in the nested model and Dweck's (1999) model at the .05 alpha level. As power increases with a corresponding increase in the degrees of freedom in a model (Schumacker & Lomax, 2010), the power and effect size (δ) for the S-B scaled difference test was calculated by comparing the degrees of freedom and parsimony in the model according to a method proposed by MacCallum, Browne, and Cai (2006). MacCallum et al. suggested calculating δ as:

$$\delta = df_{nested} \text{ x } RMSEA_{nested} - df_{modified} \text{ x } RMSEA_{modified}$$

To calculate power, the noncentrality parameter (NCP) was calculated as NCP = $(N - 1)\delta$. The NCP, sample size, and difference in degrees of freedom were then input into the G*Power 3.1 statistical software program (Buchern, Erdfelder, Faul, & Lang, 2014) to calculate the power of detecting differences in the structure of the comparative models.

Summary

The purpose of this study was to assess the role implicit theories of intelligence (or mindsets) plays in the intrapersonal motivation and academic achievement of first- and second-year students in STEM coursework at the post-secondary level. Utilizing a random sample of 2,000 students enrolled in introductory STEM courses at a public, research extensive university in the Mid-Atlantic, a self-administered survey was distributed to determine the relationships between those variables theorized to be a critical part of academic motivation and achievement. Latent factors underlying the measured variables were determined using CFA, and the factors were then subjected to

LPVA as part of a three-stage study. Model fit indices were measured and compared to assess the overall efficacy of both models. Through analysis, a final modified model emerged that was compared to the initial model using the S-B scaled difference test. Analytical procedures for both CFA and LPVA were conducted using LISREL 9.1 (Jöreskog & Sorböm, 2013), and all estimates were made using robust ML method of estimation. Statistical analyses for descriptives and checks of normality in the data were performed using SPSS 22 (IBM Corp., 2013).

CHAPTER 4

RESULTS

This study was conducted in three stages. The first stage sought to validate Dweck's (1999) motivational model of achievement at the post-secondary level among first- and second-year students enrolled in introductory STEM courses. The second stage involved testing an alternative hypothesis model to understand if measures of academic self-perception increased the absolute validity of Dweck's model. The final stage of the present study considered the findings from the first and second stages and, in alignment with the theoretical and empirical conclusions of these models, proposed and tested a modified model of mindsets and achievement motivation at the post-secondary level.

Each stage of the study progressed through the two phases as recommended by Mueller and Hancock (2010): (1) the measurement phase, where the latent variables and achievement outcome indicator were allowed to freely covary, and (2) the structural phase, where *a priori* hypothesized relationships were specified, identified, estimated, tested, and modified to fully elucidate the final models. What follows are the results of the data analysis according to this three-stage study.

Descriptive Analysis

An initial descriptive analysis of the data was conducted to highlight the overall structure of the sample population data using SPSS 22 (IBM Corp., 2013). Tables 13 and 14 provide a summary of the sample distribution and descriptive statistics for the observed variables assessed throughout the study. Most items were measured according to 6-point Likert-type scales, with positive-valence items reverse coded, where mean scores approaching six were indicative of optimal traits according to theory (e.g., growth mindset, mastery/learning goal orientation, positive beliefs about the utility of effort, effort attributions for failure, mastery-oriented academic strategies). The self-concept (SC) scale was compiled by summing the total responses from 10 eight-point Likert-type items after reverse coding negative valence SC items. Possible scores on the SC scale ranged from 0 to 80, with larger scores indicating higher domain-specific self-concept. The self-efficacy 1-5 (SE15) and self-efficacy 6-10 (SE610) scales were composed by summing the total responses for SE items 1 through 5 and 6 through 10, according to the results of the exploratory factor analysis (see Chapter 3). Possible scores for both scales ranged from 0 to 500, with larger scores indicating higher self-efficacy.

On average, the students comprising the sample were more likely to endorse growth mindsets, learning goals, positive beliefs in the utility of effort, and effort-oriented attributions for failure. Student self-reports also suggested that on average, most students tend to adopt positive, mastery-oriented achievement strategies when presented with achievement opportunities. The average student self-concept in the domain-specific areas of science, technology, engineering, or math was moderately high, $\mu = 58.27$, $s = 12.05$. Similarly, students demonstrated high self-efficacy for solving at least half of the academic problems on a given test, SE15 $\mu = 479.41$, $s = 40.47$, and moderately high self-efficacy for solving the additional problems, SE610 $\mu = 310.71$, $s = 106.34$. Finally, the sample population on average earned a B letter grade in the introductory STEM course, $\mu = 3.12$, $s = .72$.

Table 13

Distribution for 6-point Likert-type Variables and Descriptive Statistics

Item	*N*	Frequency						Mean	Std. Dev.
		(1)	(2)	(3)	(4)	(5)	(6)		
ENT1	497	17	72	128	92	135	53	3.84	1.35
ENT2	497	12	67	100	119	149	50	3.96	1.29
ENT3	497	23	92	124	106	118	34	3.62	1.33
PERF1	501	98	173	149	50	26	5	2.50	1.13
PERF2	501	41	131	168	98	57	6	3.03	1.16
PERF3	501	68	162	173	77	18	3	2.65	1.05
PERF4	501	51	135	158	91	55	11	2.99	1.22
LEARN1[1]	501	1	16	36	142	200	106	4.68	1.00
LEARN2[1]	499	4	24	101	193	145	32	4.10	1.00
LEARN3[1]	501	5	33	893	177	143	60	4.20	1.12
LEARN4[1]	501	17	48	135	164	91	46	3.80	1.21
AVOID1	499	96	187	145	41	25	5	2.45	1.11
AVOID2	500	21	72	125	103	139	40	3.77	1.33
AVOID3	500	17	59	92	128	146	58	4.00	1.31
NEGEFF1	498	14	42	94	92	179	77	4.23	1.31
NEGEFF2	499	5	11	39	84	222	138	4.85	1.05
NEGEFF3	499	6	11	29	131	215	107	4.72	1.01
NEGEFF4	499	8	36	130	131	147	47	4.03	1.17
NEGEFF5	496	2	12	80	162	182	58	4.38	0.99
POSEFF1[1]	499	7	41	107	165	128	51	4.04	1.16
POSEFF2[1]	498	9	35	50	106	191	107	4.52	1.23
POSEFF3[1]	499	1	12	23	82	208	173	5.01	0.97
POSEFF4[1]	497	21	45	85	181	122	43	3.94	1.23
HELPLES1	500	15	58	112	94	136	85	4.07	1.38
HELPLES2	496	13	63	214	107	77	22	3.48	1.11
HELPLES3	500	11	52	162	144	107	24	3.71	1.12
HELPLES4	500	14	42	130	123	152	39	3.95	1.21
EFFORT1[1]	501	3	4	10	46	207	231	5.28	0.85
EFFORT2[1]	500	1	9	13	78	253	146	5.02	0.86
POSSTAT1[1]	501	1	3	4	29	207	257	5.41	0.72
POSSTAT2[1]	501	1	3	3	37	194	263	5.41	0.73
NEGSTAT1	501	3	7	10	56	212	213	5.21	0.89
NEGSTAT2	501	10	20	72	115	199	85	4.45	1.17

Note. [1]Item reverse coded prior to tabulation of frequency or calculation of mean and standard deviation.

Table 14

Descriptive Statistics for Continuous Variables

Item	*N*	Minimum	Maximum	Range	Mean	Std. Dev.
EOCG	501	0.00	4.00	4.00	3.12	0.72
SC[ab]	496	12	80	68	58.27	12.05
SE15[b]	493	194	500	306	479.41	40.47
SE610[b]	493	2	470	468	310.71	106.34

Note. [a]Negative valence self-concept items reverse coded prior to calculating summed score. [b]Composite scores of summed responses to measured variables.

Stage One: Validating Dweck's (1999) Motivational Model of Achievement

Factor Analysis

To assess the overall structure of the latent constructs comprising the stage-one model and the suitability of the data as indicators for the corresponding latent factors, confirmatory factor analysis (CFA) for each construct was performed. Descriptive analyses for each measured variable pulled from the survey were also run to highlight the overall structure of the sample population data. CFA was conducted using LISREL 9.1 (Jöreskog & Sorböm), which simultaneously regresses the indicator variables on the latent construct. In addition, error terms and error covariances were calculated for each indicator variable to account for disturbances in sampling and measurement error. Models were tested and modified according to select fit-indices (SRMR, RMSEA, CFI, and the Satorra-Bentler [S-B; 1988] Scaled-χ^2).

Implicit Theories of Intelligence CFA. The first latent construct to be assessed was the implicit theories of intelligence (ITI) construct. Table 15 provides the summary data for this analysis. The initial model specified three measured variables as indicators for the latent ITI factor. Parameters were estimated, and the implied variance-covariance in the model was compared to the variance-covariance found in the sample data according to select fit indices. The initial implied model was calculated to be a perfect fit of the observed covariance in the sample data, S-B scaled-χ^2 = 0.00, *df = 0, p* = 1.00, indicating the model was fully saturated. Fully saturated models can be problematic, given that each data point uniquely employed to estimate all parameters (Hancock, 2014). It is only by running various regressions models can one adequately determine the true parameter fit of each effect indicator on the latent variable. However, saturated factors that demonstrate high construct reliability can be used to construct latent path models so long as the total influence of the effect indicators is adequate for the analysis (Hancock, 2014; Schumacker & Lomax, 2010) The model demonstrated high construct reliability (Coefficient *H* = .94), and path coefficients for each indicator variable were significant at the .001 alpha level. The implied model estimated six free parameters.

Table 15

Confirmatory Factor Analysis for ITI

	Indicator Variables			*H*	RMSEA
	ENT1	ENT2	ENT3		
Initial Model[a]	B = 1.00 β = .90 SE = .00 r^2 = .809	B=1.01 β = .95 SE = .02 r^2 = .894	B=.96 β = .88 SE = .03 r^2 = .768	.94	0.00

Note. H = Coefficient *H*; B = unstandardized factor loading; SE = standard error; β = standardized factor loading. SRMR and CFI indices not provided due to perfect model fit.
[a] Scaled-χ^2 = .000, *df* = 0, *p* = 1.00.

Goal Orientation CFA. Table 16 provides confirmatory factor analysis summary data for the initial specified and subsequently modified goal orientation (GOAL) constructs. The initial factor model for GOAL construct specified using all 11 indicator variables for the latent factor as provided by the *Task Goal Orientation Scale* (Midgley et al., 1998). While the model demonstrated adequate construct reliability (Coefficient *H* =

.80), the parsimony of the model was initially too high (*RMSEA* = .153). Modification indices provided by LISREL suggested adding error covariances between indicator variables, pseudo-parceling those variables that measured similar constructs: performance goal orientation, learning goal orientation, and performance-avoidant goal orientation. Model 2 was created by allowing the errors of all performance goal indicators to covary with each other. Similarly, errors between the learning goal orientation indicators and all performance-avoidant goal indicators were allowed to covary with each other. While the construct reliability increased (Coefficient *H* = .82), the RMSEA index only indicated adequate parsimony at .076. Similarly, the S-B Scaled-χ^2 of 94.90 demonstrated high significance, $p < .001$. Upon inspection of the standardized residual covariance matrix, two variables exhibited ill-explained covariance among the other factors in the model (as evidenced by residuals above 2.58): LEARN1 and LEARN2. Conceptually, the ill-explained covariance for these two factors is plausible. The LEARN1 item is the only item that specifically references students' causal attributions for studying, while all other items reference the causal attributions for completing course work. The LEARN2 item refers to difficulty: "I like course work best when it makes me think hard." Both mastery and performance can be difficult, so this item may not differentiate between performance and mastery goal orientations as well as the other effect indicators.

Model 3 (i.e., the final model) was created by eliminating the LEARN1 AND LEARN2 effect indicators from the overall model. Elimination of the two variables increased the construct reliability (Coefficient *H* = .83) while reducing the parsimonious index to an acceptable level (RMSEA = .051) indicating the estimated parameters were making useful contributions to the GOAL model. While the S-B Scaled-χ^2 remained

Table 16

Confirmatory Factor Analysis for GOAL

M	PERF1	PERF2	PERF3	PERF4	LEARN1	LEARN2	LEARN3	LEARN4	AVOID1	AVOID2	AVOID3	H	R
	Indicator Variables												
1[a]	B = 1.00 β = .58 SE = .00 r^2 =.342	B = .722 β = .41 SE = .09 r^2 =.168	B = .90 β = .56 SE = .08 r^2 =.318	B = 1.10 β = .59 SE = .11 r^2 =.349	B = .46 β = .30 SE = .11 r^2 = .090	B = .58 β = .38 SE = .09 r^2 = .144	B = .63 β = .37 SE = .10 r^2 = .139	B = .81 β = .44 SE = .11 r^2 = .195	B = .91 β = .55 SE = .09 r^2 = .299	B = 1.18 β = .59 SE = .12 r^2 = .348	B = 1.19 β = .60 SE = .12 r^2 = .358	.80	.153
2[b]	B = 1.00 β = .71 SE = .00 r^2 =.502	B = .69 β = .46 SE = .11 r^2 =.211	B = .87 β = .66 SE = .09 r^2 =.438	B = 1.21 β = .79 SE = .13 r^2 =.620	B = .22 β = .18 SE = .08 r^2 = .032	B = .33 β = .27 SE = .10 r^2 = .071	B = .41 β = .29 SE = .11 r^2 = .086	B = .58 β = .38 SE = .13 r^2 = .145	B = .61 β = .44 SE = .12 r^2 = .193	B = .62 β = .38 SE = .13 r^2 = .141	B = .68 β = .41 SE = .13 r^2 = .171	.82	.076
3[c]	B = 1.00 β = .73 SE = .00 r^2 =.531	B = .73 β = .52 SE = .11 r^2 = .267	B = .84 β = .66 SE = .09 r^2 =.431	B = 1.20 β = .81 SE = .13 r^2 =.653			B = .38 β = .28 SE = .11 r^2 =.079	B = .54 β = .37 SE = .13 r^2 =.135	B = .58 β = .43 SE = .12 r^2 =.186	B = .60 β = .37 SE = .13 r^2 =.138	B = .64 β = .40 SE = .13 r^2 =.162	.83	.051

Note. M = Model; H = Coefficient H; R = RMSEA; B = unstandardized factor loading; β = standardized factor loading; SE = standard error.

[a]SRMR = .111; CFI = .804; Scaled-χ^2 = 445.62, df = 44, $p < .001$. [b]SRMR = .051; CFI = .968; Scaled-χ^2 = 94.90, df = 29, $p < .001$.

[c]SRMR = .034; CFI = .991; Scaled-χ^2 = 31.66, df = 29, $p < .001$

Table 17

Error Covariance Terms for GOAL Final Model

Variable	PERF1	PERF2	PERF3	PERF4	LEARN3	LEARN4	AVOID1	AVOID2	AVOID3
PERF1	-								
PERF2	-.013	-							
PERF3	-.013	-.033	-						
PERF4	-.335*	-.264	-.204	-					
LEARN3					-				
LEARN4					.431**	-			
AVOID1							-		
AVOID2							.375**	-	
AVOID3							.267**	.866**	-

Note. *p < .05, two-tailed; **p < .01, two tailed.

significant at the .05 alpha level, the SRMR and CFI indices met appropriate thresholds to suggest good overall model fit. The modification index provided by LISREL suggested allowing the error variances of LEARN4 and AVOID1 to covary, yet no theoretical justification could be made to accept this recommendation. Path coefficients for each variable regression onto the GOAL construct were significant at the .01 alpha level. The implied model estimated 28 free parameters. The error covariance terms specified by the model and their significance are provided in Table 17.

Effort Beliefs CFA. CFA was likewise conducted to specify a reliable effort belief (EFFORT) construct by incorporating five negative effort and four positive effort variables from the effort beliefs subscale of the *Effort Orientation Inventory* (Dweck & Sorich, 1999). The positive effort variables were reverse coded so that high scores on all variables indicated beliefs in the utility (rather than futility) of effort. Summary data has been provided in Table 18. The initial EFFORT CFA model regressed all nine indicator variables on the latent factor. A pattern similar to the GOAL CFA emerged, whereby the model demonstrated adequate construct reliability (Coefficient H = .77) yet little parsimony (RMSEA = .144). The modification index provided by LISREL suggested parceling the variables into positive and negative groups based on the valence of the item. As parceling the item into two groups would create an under-identification error, only the errors of the five negative valence effort items were allowed to covary to create Model 2. While the parsimony index was reduced in Model 2 (RMSEA = .091), it did not reach acceptable levels of fit. In addition, the construct reliability of the EFFORT model was reduced (Coefficient H = .74) as a result of only covarying the errors of the negative effort items. The LISREL modification index suggested covarying the errors of

POSEFF2 AND POSEFF3 as well as covarying the error terms of POSEFF1 and POSEFF4. An assessment of the individual positive valence questions on the effort beliefs subscale of the *Effort Orientation Inventory* suggested that these covariances were theoretically sound: POSEFF2 and POSEFF3 seemed to address the efficacy of effort while POSEFF1 and POSEFF4 addressed issues of facing difficulty. In light of this analysis, the model was modified to incorporate these error covariances. Model 3 demonstrated an increase in construct reliability (Coefficient H = .76) and a reduction in the parsimony index (RMSEA = .055). While fit indices for Model 3 verged on thresholds of good fit, an analysis of the standardized residual covariance matrix suggested the model was incorporating two offending variables that had standardized residual levels above 2.58: NEGEFF4 and NEGEFF5. Upon reflection on the individual items, NEGEFF4 and NEFEFF5 seemed to measure beliefs in the utility of effort in dissimilar ways from the other items. While NEGEFF1, NEGEFF2, and NEGEFF3 are written to understand if students believe applied effort is a futile enterprise, NEGEFF4 and NEGEFF5 are couched in a way that suggests that whether or not one thinks effort is useful, sometimes the degree of difficulty is beyond one's ability or applied effort (e.g., "If you're not doing well at something, it's better to try something easier). Therefore, model 4 (the final model) eliminated these indicators from the factor analysis, improving both the reliability of the EFFORT construct (Coefficient H = .77) and indicating each variable was making useful contributions to the model (RMSEA = .048). Both the SRMR and CFI indexes reached satisfactory levels, and S-B Scaled-χ^2 was not significant. All coefficients for the seven regression equations were significant at the .05 alpha level. The

Table 18

Confirmatory Factor Analysis for EFFORT

M	Indicator Variables									H	RMSEA
	NEGEFF1	NEGEFF2	NEGEFF3	NEGEFF4	NEGEFF5	POSEFF1	POSEFF2	POSEFF3	POSEFF4		
1[a]	B = 1.00 β = .51 SE = .00 r^2 =.259	B = 1.04 β = .66 SE = .10 r^2 =.434	B = .14 β = .68 SE = .12 r^2 =.466	B = 1.01 β = .57 SE = .12 r^2 =.330	B = .83 β = .55 SE = .11 r^2 = .308	B = .51 β = .29 SE = .11 r^2 = .087	B = .24 β = .13 SE = .10 r^2 = .017	B = .66 β = .45 SE = .10 r^2 = .204	B = .68 β = .37 SE = .10 r^2 = .136	.77	.144
2[b]	B = 1.00 β = .21 SE = .00 r^2 =.046	B = 1.39 β = .37 SE = .30 r^2 =.137	B = 1.27 β = .35 SE = .32 r^2 =.124	B = .76 β = .18 SE = .27 r^2 =.033	B = .88 β = .25 SE = .27 r^2 = .061	B = 1.37 β = .33 SE = .41 r^2 = .109	B = 1.89 β = .43 SE = .55 r^2 = .184	B = 2.74 β = .79 SE = .75 r^2 = .624	B = 2.45 β = .56 SE = .64 r^2 = .313	.74	.091
3[c]	B = 1.00 β = .21 SE = .00 r^2 =.046	B = 1.54 β = .41 SE = .34 r^2 =.169	B = 1.32 β = .36 SE = .34 r^2 =.133	B = .81 β = .20 SE = .27 r^2 =.038	B = .89 β = .25 SE = .27 r^2 = .063	B = 1.00 β = .24 SE = .27 r^2 = .059	B = 1.23 β = .28 SE = .46 r^2 = .079	B = 2.86 β = .82 SE = .85 r^2 = .678	B = 2.21 β = .51 SE = .59 r^2 = .256	.76	.055
4[d]	B = 1.00 β = .21 SE = .00 r^2 =.046	B = 1.57 β = .41 SE = .35 r^2 =.169	B = 1.34 β = .36 SE = .34 r^2 =.133			B = .99 β = .24 SE = .34 r^2 = .059	B = 1.34 β = .28 SE = .52 r^2 = .079	B = 3.10 β = .82 SE = .96 r^2 = .678	B = 2.24 β = .51 SE = .61 r^2 = .256	.77	.048

Note. M = Model; H = Coefficient H; B = unstandardized factor loading; β = standardized factor loading; SE = standard error.

[a]SRMR = .096; CFI = .828; Scaled-χ^2 = 242.46, df = 27, p < .001. [b]SRMR = .056; CFI = .954; Scaled-χ^2 = 74.35, df = 17, p < .001.

[c]SRMR = .044; CFI = .986; Scaled-χ^2 = 32.32, df = 15, p < .01.

Table 19

Error Covariance Terms for EFFORT Final Model

Variable	NEGEFF1	NEGEFF2	NEGEFF3	POSEFF1	POSEFF2	POSEFF3	POSEFF4
NEGEFF1	-						
NEGEFF2	.479**	-					
NEGEFF3	.256**	.403**	-				
POSEFF1				-			
POSEFF2					-		
POSEFF3					.171	-	
POSEFF4							.366**

Note. ***p* < .01, two tailed.

EFFORT construct estimated 19 free parameters. Error covariance terms for the final EFFORT construct and their significance are provided in Table 19.

Failure Attribution and Achievement Strategies CFA. CFA was also run to specify a reliable construct for students' failure attribution (FAIL). Four helpless and two effort attribution measures from the failure attribution subscale of the *Effort Orientation Inventory* (Dweck & Sorich, 1999) were regressed on the FAIL latent factor. Summary data has been provided in Table 20. For the initial model, the measurement equation for HELPLES3 produced a standardized loading larger than 1 and a negative error variance indicating a Heywood Case. Schumacker and Lomax (2010) suggest that Haywood Cases be resolved by reducing the communality of the offending variables. The standardized residual covariance matrix suggested a linear dependency of HELPLES1 on HELPLES4, so HELPLES1 was eliminated from the factor analysis in Model 2. Model 2 demonstrated inadequate construct reliability (Coefficient H = .60) and parsimony (RMSEA = .204). An analysis of the standardized residual covariance matrix confirmed that a significant relationship between EFFORT1 and EFFORT2 existed, while R^2 values suggested that the latent factor was doing a poor job of defining the entire group of variables. The S-B Scaled-χ^2 value of 66.84 (df = 5, p < .001) reiterated the fact that the variance-covariance measured by the indicator variables of the sample data was significantly different from that of the implied model. Theoretically, the optimal solution for modifying the model was to remove the helpless attribution subscales leaving the highly correlated effort items (Spearman r^2 = .435), yet this modification would under-identify the model. To remedy the identification issue, the FAIL construct was modeled with the achievement strategies (STRAT) construct as *a priori* theory suggested the attributions students apply to their failure are related to the strategies they use to succeed academically (Dweck & Sorich, 1999).

Table 20

Confirmatory Factor Analysis for FAIL

M	Indicator Variables						*H*	R
	HELPLES 1	HELPLES 2	HELPLES 3	HELPLES 4	EFFORT 1	EFFORT 2		
1[a]	B = 1.00 β = .50 SE = .00 r^2 =.251	B = .40 β = .25 SE = .07 r^2 =.061	B = 1.76 β = 1.09 SE = .33 r^2 =1.181	B = .61 β = .35 SE = .09 r^2 =.122	B = -.03 β = -.02 SE = .05 r^2 = .001	B = .00 β = .00 SE = .08 r^2 = .000	--	.165
2[b]		B = 1.00 β = .41 SE = .00 r^2 =.170	B = 1.64 β = .67 SE = .34 r^2 =.448	B = 1.50 β = .57 SE = .28 r^2 =.321	B = .05 β = .03 SE = .10 r^2 = .001	B = .00 β = .00 SE = .11 r^2 = .000	.60	.204

Note. M = Model; *H* = Coefficient *H*; R = RMSEA; B = unstandardized factor loading; β = standardized factor loading; SE = standard error.

[a]SRMR = .105; CFI = .772; Scaled-χ^2 = 97.33, *df* = 9, *p* < .001. [b]SRMR = .115; CFI = .727; Scaled-χ^2 = 66.84, *df* = 5, *p* < .001. [c]Coefficient *H* cannot be measured for Haywood Cases.

CFA was therefore conducted with two covaried latent factors: FAIL and STRAT. The two effort-attribution measured variables served as indicators for the FAIL construct, while two positive valence items (POSSTAT1 and POSSTAT2) and two negative valence items (NEGSTAT1 and NEGSTAT2) served as indicators for STRAT. Summary data for the CFA has been provided in Table 21. The initial model demonstrated high construct reliability (Coefficient *H* = .92), yet the model was not parsimonious (RMSEA = .144). An inspection of the standardized residual covariance matrix suggested NEGSTAT2 did not uniquely serve as an indicator of academic strategies according to a standardized residual covariance with EFFORT2 measuring 2.03. Similarly, a codependence between NEGSTAT2 and NEGSTAT1 was indicated according to a

Table 21

Confirmatory Factor Analysis for FAIL and STRAT

M	FAIL Indicator Variables		STRAT Indicator Variables				*H*	R
	EFFORT1	EFFORT2	POSSTAT1	POSSTAT2	NEGSTAT1	NEGSTAT2		
1[a]	B =1.00 β = .67 SE = .00 r^2 =.455	B = .92 β = .61 SE = .09 r^2 =.372	B = .67 β = .93 SE = .05 r^2 =.864	B = .64 β = .87 SE = .05 r^2 =.751	B = .43 β = .48 SE = .05 r^2 = .229	B = .29 β = .24 SE = .05 r^2 = .060	.92	.144
2[b]	B = 1.00 β = .68 SE = .00 r^2 =.456	B = .92 β = .61 SE = .09 r^2 =.371	B = .68 β = .94 SE = .05 r^2 =.892	B = .63 β = .86 SE = .05 r^2 =.732	B = .42 β = .46 SE = .05 r^2 = .216		.92	.043

Note. M = Model; *H* = Coefficient *H*; R = RMSEA; B = unstandardized factor loading; β = standardized factor loading; SE = standard error.

[a]SRMR = .072; CFI = .949; Scaled-χ^2 = 69.75, *df* = 8, *p* < .001. [b]SRMR = .017; CFI = .998; Scaled-χ^2 = 6.31, *df* = 4, *p* = .177.

standardized residual covariance of 6.20. Conceptually, this discrepancy was readily apparent upon further review of each academic strategy question. While NEGSTAT1, POSTAT1, and POSSTAT2 provided realistic strategies college students might employ, the option provided by NEGSTAT2 seems more unrealistic: “I would try not to take this subject ever again.” Most degrees in college require enrollment in multiple courses within the same subject domain. The decision to not take a course in a subject may require students to change their major declarations. As the sample population was taking introductory STEM courses that led to future coursework or were required for STEM degrees, it seems unlikely that students would chose this effort-avoidant strategy due to the high cost of having to switch majors. To account for the discrepancy between the item variances, NEGSTAT2 was removed from the modified Model 2. With this modification, Model 2 retained its high construct reliability (Coefficient *H* = .92) and met the thresholds for all other goodness-of-fit indices (RMSEA = .043; SRMR = .017; CFI =

.998; S-B Scaled-$\chi^2 = 6.31$, , $df = 4$, $p = .177$) to suggest the two latent factors were sufficiently and uniquely contributing to the five measured variables. Path coefficients for the five regression equations were significant at the .01 alpha level. Eleven free parameters were estimated between the FAIL and STRAT constructs. Pearson r^2 correlation between the FAIL and STRAT latent factors measured .80, $p < .001$.

Phase One: Measurement Model Analysis

Once the individual constructs that compose Dweck's (1999) motivational model of achievement were confirmed, validation of the overall model began according to the recommended first phase of analysis: the measurement model evaluation (Hancock & Mueller, 2010). In this phase of analysis, the model was temporarily specified to allow all latent factors to freely covary. The analysis then proceeded to identify, estimate, test, and modify the model prior to entering the second stage: structural model analysis.

Model specification. The measurement model in stage one of this study was specified as consisting of the five latent constructs previously subjected to confirmatory factor analysis: implicit theories of intelligence (ITI), goal orientation (GOAL), effort beliefs (EFFORT), failure attribution (FAIL), and achievement strategies (STRAT). In addition, the model also included the endogenous outcome criterion of academic achievement (AA) as identified by the end-of-course-grade earned as part of the enrolled classes that constituted the study's sampling frame. As suggested by Hancock & Mueller (2010), all latent constructs were allowed to freely covary. The initial measurement model for phase one included 25 observed variables. Table 22 provides the Spearman correlation coefficients and two-tailed significance estimates among the observed variables for the validation model. As noted previously, the correlations between the ITI effect indicators ENT1, ENT2, and ENT3 were large enough to suggest multicollinearity. However, all three variables were included due to theoretical and analytical considerations. As mentioned in Chapter 3, each variable theoretically captures a discrete aspect of the fixed entity mindset. Analytically, elimination of any of the variables would cause underidentification.

Table 22

Spearman Correlation Coefficients and Significance (Two-tailed) among Observed Variables in Stage One

Variable	ENT1	ENT2	ENT3	PERF1	PERF2	PERF3
ENT1	---					
ENT2	.844[a] .000[b]	---				
ENT3	.783 .000	.824 .000	---			
PERF1	.250 .000	.237 .000	.212 .000	---		
PERF2	.169 .000	.152 .001	.169 .000	.341 .000	---	
PERF3	.134 .003	.126 .005	.101 .023	.464 .000	.299 .000	---
PERF4	.210 .000	.198 .000	.187 .000	.321 .000	.221 .000	.357 .000
LEARN3	.185 .000	.162 .000	.141 .002	.252 .000	.047 .289	.157 .000
LEARN4	.180 .000	.188 .000	.147 .001	.258 .000	.107 .017	.202 .000
AVOID1	.063 .157	.073 .104	.102 .022	.297 .000	.309 .000	.314 .000
AVOID2	.063 .157	.073 .104	.102 .022	.297 .000	.309 .000	.314 .000
AVOID3	.134 .003	.170 .000	.127 .004	.245 .000	.234 .000	.263 .000
NEGEFF1	.218 .000	.152 .001	.133 .003	.203 .000	.134 .003	.168 .000
NEGEFF2	.362 .000	.380 .000	.317 .000	.139 .002	.153 .001	.136 .002
NEGEFF3	.318 .000	.342 .000	.288 .000	.128 .004	.104 .020	.130 .004
POSEFF1	.085 .057	.119 .008	.103 .021	.087 .052	-.003 .949	.189 .000
POSEFF2	.040 .372	.070 .116	.046 .306	-.114 .011	-.067 .133	-.080 .072

POSEFF3	.193 .000	.234 .000	.142 .001	-.075 .093	-.058 .197	-.002 .960
POSEFF4	.150 .001	.164 .000	.163 .000	.076 .090	-.046 .304	.081 .070
EFFORT1	.095 .-34	.093 .038	.069 .121	-.048 .282	-.055 .215	-.004 .928
EFFORT2	.135 ..003	.152 .001	.092 .039	-.085 .058	.000 .998	.040 .368
POSSTAT1	.089 .047	.122 .006	.129 .004	-.067 .132	.030 .505	.036 .422
POSSTAT2	.086 .054	.133 .003	.124 .006	-.057 .203	-.018 .683	.048 .279
NEGSTAT1	.149 .001	.128 .004	.135 .002	.135 .002	.055 .218	.145 .001
EOCG	.040 .371	.004 .932	.008 .858	-.025 .574	-.033 .460	.008 .855

Variable	PERF4	LEARN3	LEARN4	AVOID1	AVOID2	AVOID3
PERF4	---					
LEARN3	.216 .000	---				
LEARN4	.338 .000	.413 .000	---			
AVOID1	.300 .000	.085 .058	.161 .000	---		
AVOID2	.262 .000	.102 .023	.146 .001	.401 .000	---	
AVOID3	.324 .000	.151 .001	.122 .006	.343 .000	.648 .000	---
NEGEFF1	.185 .000	.104 .020	.042 .343	.127 .004	.265 .000	.266 .000
NEGEFF2	.170 .000	.239 .000	.143 .001	.090 .044	.191 .000	.264 .000
NEGEFF3	.158 .000	.170 .000	.085 .056	.045 .311	.179 .000	.240 .000
POSEFF1	.260 .000	.297 .000	.300 .000	.101 .023	.092 .041	.179 .000
POSEFF2	.043 .342	.092 .039	.078 .083	-.087 .052	-.026 .564	.048 .279
POSEFF3	.004 .923	.200 .000	.139 .002	-.014 .754	.023 .611	.087 .051
POSEFF4	.185 .000	.259 .000	.277 .000	.025 .584	.090 .045	.129 .004
EFFORT1	.029 .514	.107 .017	.077 .085	-.176 .000	.014 .747	.003 .046
EFFORT2	.047 .295	.098 .028	.122 .006	-.092 .040	.010 .831	.029 .511
POSSTAT1	.065 .147	.156 .000	.056 .214	-.052 .250	.064 .154	.102 .023
POSSTAT2	.089 .046	.156 .000	.097 .031	-.044 .328	.072 .107	.101 .024

NEGSTAT1	.165	.180	.064	.013	.123	.181
	.000	.000	.152	.779	.006	.000
EOGC	.003	.046	-.001	-.017	.008	.041
	.944	.300	.977	.698	.866	.357

Variable	NEGEFF1	NEGEFF2	NEGEFF3	POSEFF1	POSEFF2	POSEFF3
NEGEFF1	---					
NEGEFF2	.411	---				
	.000					
NEGEFF3	2.76	.522	---			
	.000	.000				
POSEFF1	.160	.158	.176	---		
	.000	.000	.000			
POSEFF2	.041	.040	.096	.143	---	
	.365	.369	.031	.001		
POSEFF3	.174	.350	.341	.210	.409	---
	.000	.000	.000	.000	.000	
POSEFF4	.159	.179	.240	.397	.225	.419
	.000	.000	.000	.000	.000	.000
EFFORT1	.045	.123	.172	.088	.262	.223
	.312	.006	.000	.049	.000	.000
EFFORT2	.094	.189	.107	.124	.213	.203
	.036	.000	.016	.006	.000	.000
POSSTAT1	.111	.200	.233	.265	.300	.314
	.013	.000	.000	.000	.000	.000
POSSTAT2	.131	.205	.199	.292	.304	.281
	.003	.000	.000	.000	.000	.000
NEGSTAT1	.250	.251	.299	.224	.192	.208
	.000	.000	.000	.000	.000	.000
EOCG	-.002	.044	.082	.039	.152	.079
	.971	.321	.067	.390	.001	.079

Variable	POSEFF4	EFFORT1	EFFORT2	POSSTAT1	POSSTAT2	NEGSTAT1
POSEFF4	---					
EFFORT1	.176	---				
	.000					
EFFORT2	.172	.435	---			
	.000	.000				
POSSTAT1	.287	.437	.442	---		
	.000	.000	.000			
POSSTAT2	.270	.390	.363	.806	---	
	.000	.000	.000	.000		
NEGSTAT1	.222	.267	.294	.511	.493	---
	.000	.000	.000	.000	.000	
EOCG	.072	.099	.129	.233	.235	.084
	.107	.026	.004	.000	.000	.060

Note. N = 501.

[a] Spearman correlation coefficient; [b] Alpha level (two-tailed).

Error terms for the effect indicators were allowed to covary according to the results of the conducted factor analyses. The error term for the measured end-of-course-grade (EOCG) was set to zero, whereby the standardized loading for the indicator on the AA latent factor was equal to one. In total, the measurement model specified the following: 25 path coefficients, 14 correlations between latent factors, 25 error variances for the effect indicators, and 15 error covariances between effect indicators.

Model identification and estimation. In total, the initial measurement model specified 79 parameters to be estimated. With 25 observed variables, the number of distinct values in the sample data matrix exceeded the number of parameters to be estimated, indicating over-identification of the model. Furthermore, empirical underidentification did not prove to be an issue for the specified model.

Figure 13 depicts the initial standardized parameter estimates of the stage-one measurement model and corresponding factor loadings, and Table 23 provides correlations among the latent factors for the model. Significant correlations among the latent factors ranged between .15 and .80, $p < .01$. The attributions students make for failure and the strategies they would choose to employ to overcome that failure were highly correlated, $r = .80$, $p < .01$. While multicollinearity between latent factors can present estimation issues when the two collinear factors are modeled together to predict a third factor (Schwarz et al., 2014), FAIL and STRAT served as independent variables in each structural model that did not simultaneously influence any endogenous construct. A moderate correlation was identified comparing students' implicit theories of intelligence (ITI) and the goal orientations they exhibit, $r = .36$, $p < .01$. Similarly, students' ITI and their belief in the utility of effort was also moderately correlated, $r = .49$, $p < .01$.

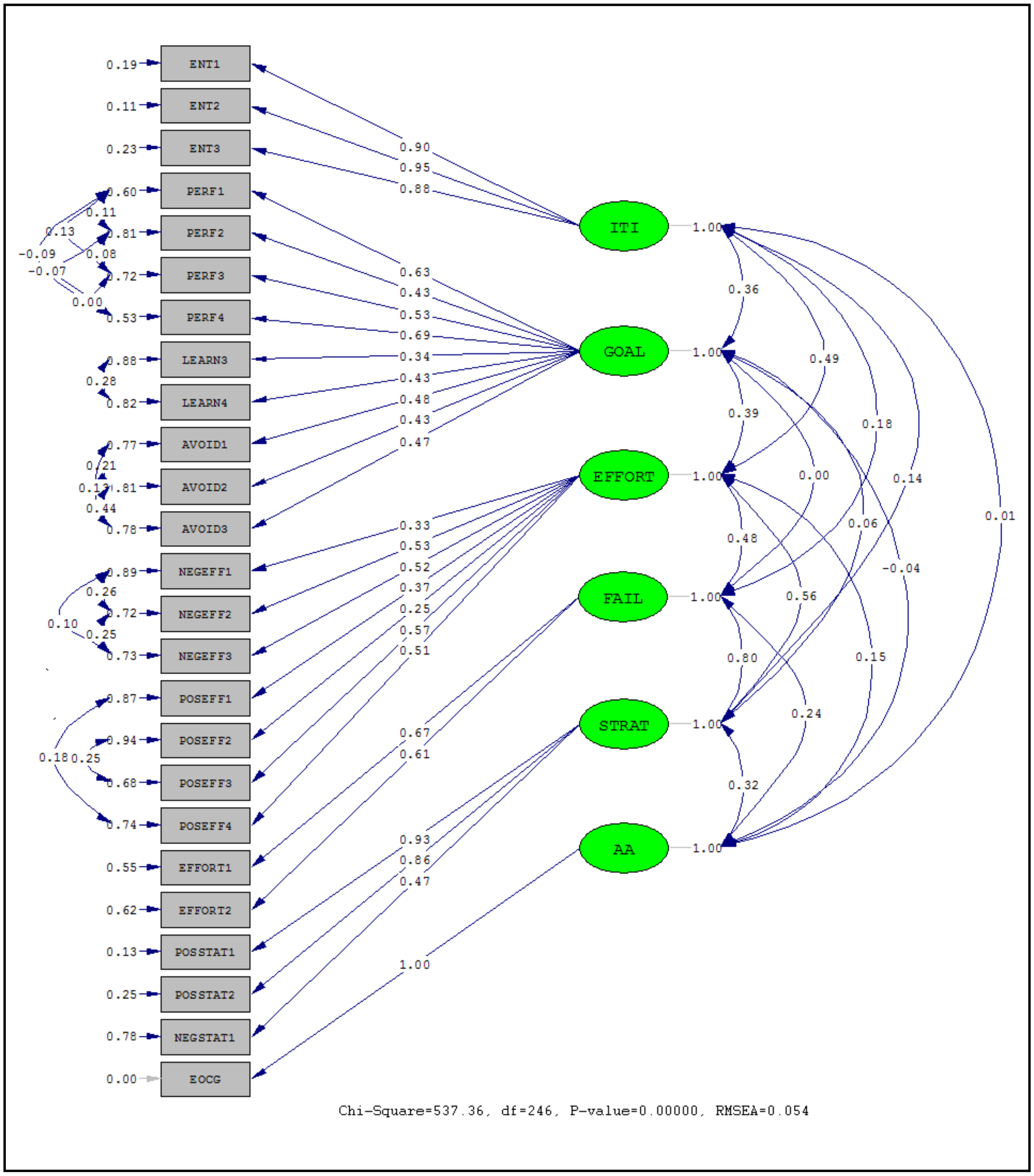

Figure 13. Standardized parameter estimates of stage-one measurement modeling for Dweck's (1999) motivational model of achievement (*N* = 501). ITI = implicit theories of intelligence; GOAL = goal orientation; EFFORT = beliefs about the utility of effort; FAIL = failure attributions; STRAT = achievement strategies; AA = academic achievement.

Students belief in the utility of effort was also moderately correlated with three other latent factors: the goal orientations they exhibit, $r = .39$, $p < .01$; their attributions for failure, $r = .48$, $p < .01$; and the academic strategies they adopt in the face of failure, $r = .56$, $p < .01$.

Table 23

Correlations and Standard Errors among Latent Factors for Stage-one Measurement Model

Variable	ITI	GOAL	EFFORT	FAIL	STRAT	AA
ITI	1.000					
GOAL	0.361** (0.048)	1.000				
EFFORT	0.485** (0.056)	0.387** (0.070)	1.000			
FAIL	0.179** (0.066)	0.033 (0.088)	0.483** (0.072)	1.000		
STRAT	0.145** (0.053)	0.061 (0.074)	0.558** (0.051)	0.803** (0.050)	1.000	
AA	0.007 (0.044)	-0.037 (0.058)	0.147** (0.055)	0.243** (0.069)	0.320** (0.049)	1.000

Note. $N = 501$. ITI = implicit theories of intelligence; GOAL = goal orientation; EFFORT = effort beliefs; FAIL = failure attribution; STRAT = academic strategies; AA = academic achievement.

$^{**}p < .01$, two-tailed.

As CFA had been previously conducted for the individual latent constructs, it was expected that the measurement model would also provide evidence for appropriate validity and reliability. Table 24 provides the estimates for each effect indicator, including the standardized factor loadings (or construct validity estimates; Schumacker & Lomax, 2010), error variance, and indicator reliability (or the square of the standardized factor loading; R^2), as well as the calculated coefficient H measure of construct reliability. Excluding the AA indicator EOCG (whose factor loading was set to one and error variance was set to zero), standard factor loadings for each effect indicator ranged from .25 (POSEFF2) to .95 (ENT2), all significant at the .05 alpha level. Similarly, the error variance for POSEFF2 (.94) and ENT2 (.11) served as the limits for the error variance range.

Table 24

Standardized Factor Loadings and Reliability Estimates for Stage-one Measurement Model Constructs

Construct	Indicator Variables	Standardized Factor Loading	Standardized Error Variance	Indicator Reliability (R^2)	Coefficient *H*
ITI	ENT1	.90	.19	.81	.94
	ENT2	.95	.11	.90	
	ENT3	.88	.23	.77	
GOAL	PERF1	.63	.60	.40	.77
	PERF2	.43	.81	.19	
	PERF3	.53	.72	.29	
	PERF4	.69	.53	.47	
	LEARN3	.34	.88	.12	
	LEARN4	.43	.82	.18	
	AVOID1	.48	.77	.23	
	AVOID2	.43	.81	.19	
	AVOID3	.47	.78	.22	
EFFORT	NEGEFF1	.33	.89	.11	.66
	NEGEFF2	.53	.72	.28	
	NEGEFF3	.52	.73	.27	
	POSEFF1	.37	.87	.13	
	POSEFF2	.25	.94	.06	
	POSEFF3	.57	.68	.32	
	POSEFF4	.51	.74	.26	
FAIL	EFFORT1	.67	.55	.45	.58
	EFFORT2	.61	.62	.38	
STRAT	POSSTAT1	.93	.13	.87	.90
	POSSTAT2	.86	.25	.75	
	NEGSTAT1	.47	.70	.22	
AA	EOCG	1.00	.00	1.00	--

Note. $N = 501$

R^2 values for the effect indicators varied widely from .06 to .92. Importantly, each construct had at least one effect indicator demonstrate moderate reliability, $R^2 > .30$

(Schumacker & Lomax, 2010). All effect indicators for the ITI construct demonstrated high reliability, with the lowest indicator (ENT3) providing a .77 reliability estimate. PERF4 (R^2 = .47) and PERF1 (R^2 = .40) served as the most reliable indicators for the GOAL construct. POSEFF3 (R^2 = .40) demonstrated the highest reliability for the EFFORT construct, while POSEFF 2 (R^2 = .06) demonstrated the lowest reliability for the EFFORT construct; however, the difference in the reliability estimates for these constructs could be attributed to the shared covariance between these indicators as specified in the measurement model. EFFORT1 (R^2 = .45) served as the most reliable indicator for the FAIL construct, and both POSTAT1 (R^2 = .87) and POSTAT2 (R^2 = .75) demonstrated high reliability as indicators for the STRAT construct. Reliability as measured by coefficient *H* for each latent construct ranged from .90 (STRAT) to .58 (FAIL).

Model testing. Overall, the initial measurement model for phase one of the study demonstrated acceptable fit, suggesting the sample covariance matrix was sufficiently reproduced by the implied measurement model. The absolute fit of the model, whereby the implied covariance fit the covariance present in the sample population, reached an acceptable level, SRMR = .073. Similarly, the measurement model suggested the noncentral distribution of the data was adequately improved when the implied model was incrementally compared to the null distribution, CFI = .958. Finally, the parsimony of the model was considered to be a good fit, RMSEA = .054, 90% CI [.049, .060]. The S-B scaled-χ^2 of 537.36 (df = 246) was significant at the .001 alpha level indicating the implied variance-covariance in the measurement model may differ from the observed variance-covariance in the sample; however, this index was disregarded given the strength of the absolute, incremental, and parsimonious indices. A review of the standardized residual covariance matrix and modification indices provided by LISREL 9.1 revealed that there were a number of opportunities to reduce the S-B scaled-χ^2 statistic. However, the present study refrained from making further modifications to the model in order to assess the validity of Dweck's (1999) hypothesized relationships. After review of the provided goodness-of-fit indices and opportunities for modification, the initial measurement model was adopted as the final measurement model for phase one, suggesting the measured variance-covariance in the sample data was not significantly different from that of the implied measurement model. Having appropriately specified the measurement variables for the model and tested their goodness-of-fit, it was decided that the structural analysis of the model could proceed.

Phase Two: Structural Model Analysis

Phase two of stage one sought to assess the structural relationships between the latent factors that were hypothesized by Dweck's (1999) in her motivational model of achievement: namely the effect of implicit theories of intelligence on intrapersonal motivation variables including goal orientation, beliefs about the efficacy of effort, failure attributions, and achievement strategies. As part of the structural model analysis phase, the theoretical relationships between the latent factors were initially specified. Model parameters were then identified, estimated, and tested according to relevant goodness-of-fit statistics. The final structural model was adopted based on an analysis of the goodness-of-fit indices and relative weights of the estimated parameters.

Model specification. The stage-one structural model was initially specified according to the theory proposed by Dweck (1999). Dweck hypothesized that students' implicit theories of intelligence (ITI) exert an influence on goal orientation (GOAL) and beliefs about the utility of effort (EFFORT). In turn, both GOAL and EFFORT influence the achievement strategies (STRAT) students adopt in academic settings. Additionally, Dweck's hypothesis supposes the relationships between EFFORT and STRAT is also mediated by the causes students attribute to failure (FAIL). Finally, (STRAT) is believed to directly influence students' academic achievement outcomes. These causal relationships were incorporated into the model to reflect the full structural model.

The initial stage-one structural model consisted of the six latent factors and 25 effect indicators (i.e., measured variables) in the measurement model. Again, error terms for some effect indicators were allowed to covary in accordance with the prior factor analysis. The error variance for EOCG was set to zero, ostensibly fixing the standardized loading for the indicator on AA to one. Reference variables for the other five latent constructs included ENT1, PERF1, NEGEFF1, EFFORT1, and POSSTAT1 accordingly. Overall, the initial structural model specified the following: 7 structural equations composed of 7 structure coefficients and 7 disturbance terms, 1 exogenous variable variance, 19 path coefficients (with 6 factor loadings fixed to one), 24 error variances for the effect indicators, and 15 error covariances between effect indicators.

Model identification and estimation. The initial structural model identified 71 parameters to be estimated. As the structural model retained the same number of observed variables from the measurement model (25), the number of distinct variables in the sample data matrix also exceeded the number of parameters to be estimated in the structural model. With no issues of empirical underidentification, the excess of data points presented an over-identified model.

Maximum likelihood (ML) was employed to estimate the parameters of the stage-one structural model. The LISREL output in Figure 14 depicts the unstandardized parameter estimates of the model, while Tables 25, 26, and 27 list the standardized ML estimates for the measured variables, specified covariances between measured variables, and structural relationships between the latent factors accordingly. Constraints implied by the structure of the model had the effect of increasing the construct reliability of the GOAL, EFFORT, and STRAT constructs. All estimated factors loadings remained significant at the .01 alpha level, and most of the specified error covariances remained significant. The PERF1 covariances with PERF2 (cov = .049) AND PERF3 (cov = .072) became non-significant, while the PERF4 covariances with PERF1 (cov = -.233) and PERF2 (cov = -.191) were significant at the .05 alpha level.

In general, the relative magnitude and direction for most parameter estimates for the phase-one structural model seemed to conform to *a priori* theory. With only one exception, the structural relationships between specified latent factors were all significant at the .05 alpha level. Incremental implicit theories of intelligence (or growth mindsets) had a positive influence on students' adoption of learning goal orientations ($\beta = .34$) and positive beliefs about the utility of effort ($\beta = .42$). Beliefs about effort, in turn, strongly influenced how students attribute causes to failure ($\beta = .47$) and their choice of positive achievement strategies ($\beta = .52$) through a direct effect ($\beta = .19$) and an indirect effect mediated by failure attributions ($\beta = .33$). Students' attribution of lack of effort to failure had a positive influence on the achievement strategies they would adopt in future achievement scenarios ($\beta = .71$). Finally, increased academic achievement was positively influenced by the mastery-oriented achievement strategies adopted by students ($\beta = .32$).

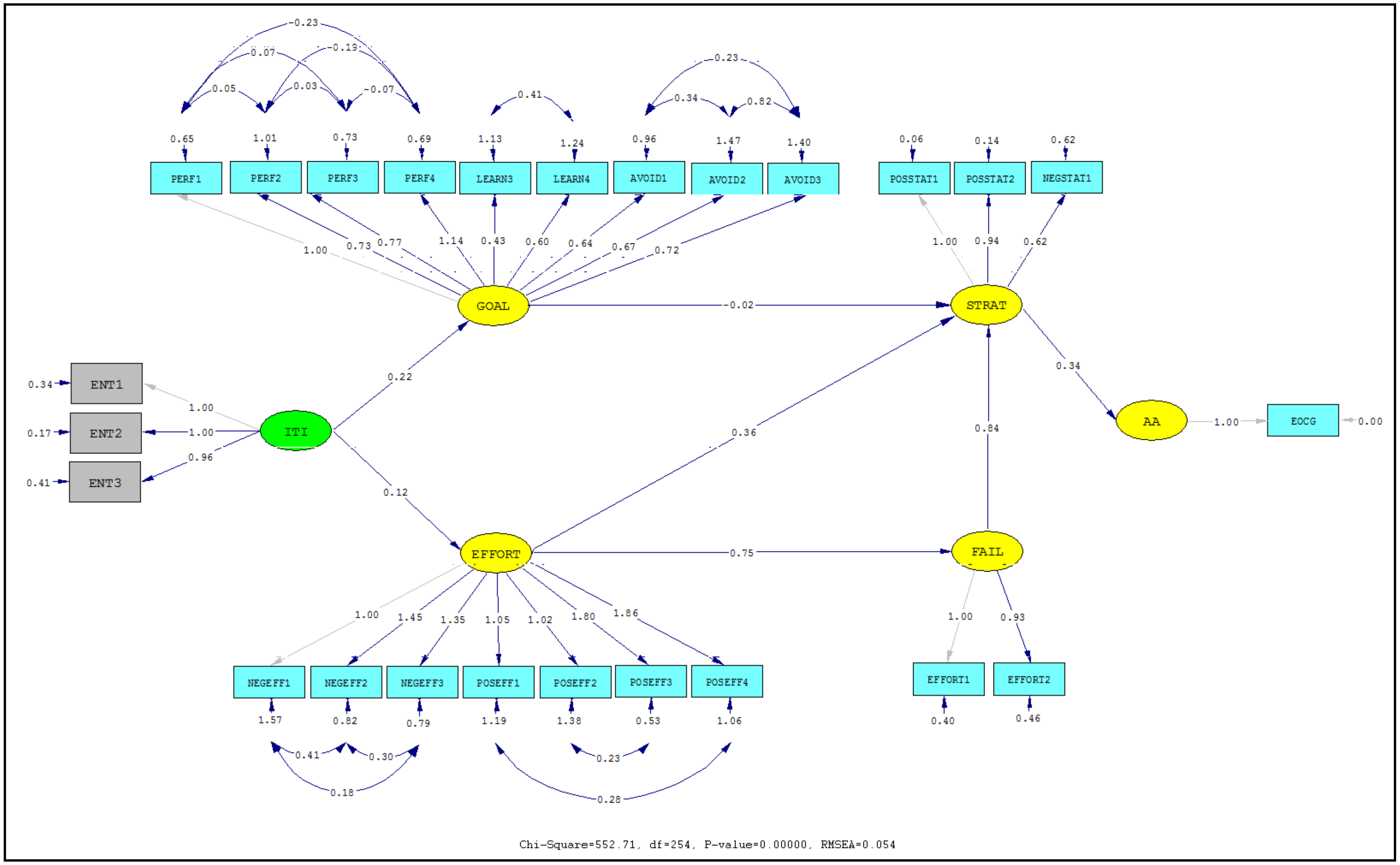

Figure 14. Unstandardized parameter estimates of stage-one structural modeling for Dweck's (1999) motivational model of achievement ($N = 501$). ITI = implicit theories of intelligence; GOAL = goal orientation; EFFORT = beliefs about the utility of effort; FAIL = failure attributions; STRAT = achievement strategies; AA = academic achievement.

The parameter estimates suggested students' adoption of learning goal orientations had a slightly negative effect on their achievement strategies (β = -.03), yet the implied covariance of this path was not significant at the .05 alpha level, indicating goal orientation did not play a mediating role in the relationship between implicit theories of intelligence, achievement strategies, and academic achievement. This finding is not necessarily surprising given the aforementioned discrepancies found in the literature

Table 25

Factor Loadings and Reliability Estimates for Stage-one Structural Model Constructs

Construct	Indicator Variables	Standardized Factor Loading	Standardized Error Variance	Indicator Reliability (R^2)	Coefficient *H*
ITI	ENT1	.90**	.19	.81	.94
	ENT2	.95**	.11	.90	
	ENT3	.88**	.23	.77	
GOAL	PERF1	.70**	.51	.49	.80
	PERF2	.50**	.75	.25	
	PERF3	.58**	.66	.34	
	PERF4	.74**	.46	.54	
	LEARN3	.31**	.91	.09	
	LEARN4	.39**	.84	.16	
	AVOID1	.46**	.79	.21	
	AVOID2	.40**	.84	.16	
	AVOID3	.43**	.81	.19	
EFFORT	NEGEFF1	.27**	.92	.08	.68
	NEGEFF2	.49**	.76	.25	
	NEGEFF3	.48**	.77	.23	
	POSEFF1	.33**	.89	.11	
	POSEFF2	.30**	.91	.09	
	POSEFF3	.66**	.56	.44	
	POSEFF4	.54**	.71	.29	
FAIL	EFFORT1	.67**	.55	.45	.58
	EFFORT2	.61**	.62	.38	
STRAT	POSSTAT1	.94**	.12	.88	.91
	POSSTAT2	.86**	.26	.74	
	NEGSTAT1	.47**	.78	.22	
AA	EOCG	1.00	.00	1.00	

Note. $N = 501$.

$^{**}p < .01$.

Table 26

Error Covariance Terms for Stage-one Structural Model

Variable	PERF1	PERF2	PERF3	LEARN3	AVOID1	AVOID2
PERF2	.049					
PERF3	.072	.028				
PERF4	-.233*	-.191*	-.072			
LEARN4				.407**		
AVOID2					.340**	
AVOID3					.232**	.824**
Variable	NEGEFF1	NEGEFF2	POSEFF1	POSEFF2		
NEGEFF2	.407**					
NEGEFF3	.179**	.305**				
POSEFF3				.232**		
POSEFF4			.276**			

Note. **p* < .05, two-tailed; ***p* < .01, two-tailed.

Table 27

Structural Relationships Between Latent Factors in Stage-One Model

	R^2	Path Coefficients					Error Variance
		ITI	GOAL	EFFORT	FAIL	STRAT	
GOAL							
B		0.224					
t value	.12	6.490					.552**
p value		.000					
β		0.34					
EFFORT							
B		0.124					
t value	.18	4.005					.105*
p value		.000					
β		0.42					
FAIL							
B				0.752			
t value	.22			3.467			.252**
p value				.001			
β				0.47			
STRAT							
B			-0.0247	0.357	0.845		
t value	.67		-0.618	2.336	7.598		.151**
p value			.537	.020	.00		
β			-0.03	0.19	0.71		
AA							
B						0.337	
t value	.10					6.722	.461**
p value						.00	
β						0.32	

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

suggesting goal orientation may play a negligible role in the hypothesized structural relationship between implicit theories of intelligence and academic achievement.

Overall, the variance for each endogenous factor was adequately explained by the regressed factors. Implicit theories of intelligence accounted for 12 percent of the variance in goal orientation (R^2 = .12) and 18 percent of the variance in effort beliefs (R^2 = .18). Effort beliefs accounted for 22 percent of the variance in failure attributions ((R^2 = .22). The three predictors for achievement strategies, goal orientation, effort beliefs, and failure attributions together accounted for 67 percent of the factor's variance (R^2 = .67). Yet in total, the model only accounted for 10 percent of the variance in academic achievement (R^2 = .10).

Model testing. Tests of goodness-of-fit for the initial stage-one structural model were mixed. Acceptable levels of both incremental and parsimonious fit were reached: comparison of the implied covariance of the structural model to the null distribution improved the noncentral distribution of the data, CFI = .957, while each of the variables were making useful contributions to the model, RMSEA = .054, 90% CI [.050, .060]. However, the absolute fit of the implied covariance in the structural model on the covariance in the sample data did not meet acceptable thresholds for proper absolute fit, SRMR = .082, suggesting the model does not serve as a tenable explanation of achievement motivation. The inadequate absolute fit of the structural model was most likely due to the non-significant contribution made by the GOAL construct on STRAT. Having hypothesized a significant relationship between these constructs, failure to replicate this implied covariance of the model in the sample data would decrease the likelihood of achieving overall fit. A significant S-B scaled-χ^2 of 552.711, $df = 254$, $p < .001$ confirmed inadequate overall fit of the initial model.

Inspection of the standardized residual covariance matrix revealed large residuals between the effect indicators for GOAL and the effect indicators for both EFFORT and STRAT ranging from 2.658 to 5.874. These values suggested that the GOAL construct was misspecified within the model. Other than completely removing the construct, a review of the literature revealed no other theories that would suggest an alternative relationship of the GOAL construct in Dweck's (1999) hypothesized model. Further review of the modification indices provided by LISREL failed to suggest any path or error covariance adjustments that were theoretically sound. In light of these findings, the initial structural model was adopted as the final model for stage one of the study. As specified, the final stage-one structural model demonstrated an implied covariance that did not fit the covariance present in the sample data. It was determined that Dweck's (1999) motivational model of achievement could not be validated due to the inability to improve the absolute fit of the model without violating theoretical considerations. As originally specified, Dweck's motivational model of achievement at the collegiate level did not meet acceptable thresholds for goodness-of-fit and therefore cannot serve as a tenable explanation of achievement motivation at the post-secondary level.

Stage Two: Alternative Hypothesis Model

Factor Analysis of Academic Self-Perception

In stage two of the study, a seventh construct was introduced to Dweck's (1999) motivational model of achievement: academic self-perception (ASP). To assess whether accounting for ASP improves our understanding of the relationships between ITI and motivation, the suitability of the measured variables as indicators of ASP was first analyzed. CFA was once again conducted using LISREL 9.1 (Jöreskog & Sorböm, 2013) to regress the three indicator variables – SC, SE15 and SE610 – on the ASP latent factor. Table 4.17 summarizes the data for this analysis. The implied model was tested and calculated to be a perfect fit of the observed covariance in the sample data, S-B scaled-χ^2 = 0.00, p = 1.00, indicating a fully saturated model. The model exhibited acceptable construct reliability (Coefficient H = .79), and all path coefficients for the effect indicators were significant at the .001 alpha level. Six free parameters were estimated by the implied model.

Table 28

Confirmatory Factor Analysis for ASP

	Indicator Variables			H	RMSEA
	SC	SE15	SE610		
Initial Model[a]	B = 1.00 β = .45 SE = .00 r^2 = .21	B = 5.21 β = .71 SE = .65 r^2 = .50	B = 16.59 β = .85 SE = 2.32 r^2 = .73	.79	0.00

Note. H = Coefficient H; β = standardized factor loading. SRMR and CFI indices not provided due to perfect model fit.

[a] Scaled-χ^2 = .000, df = 0, p = 1.00.

Phase One: Measurement Model Analysis

Having confirmed the ASP factor as reliable, stage two of the study began by re-running the measurement model analysis of the stage-one model with the addition of the ASP factor. All latent factors were allowed to freely covary, and both estimates and tests of goodness-of-fit were conducted prior to specifying structural relationships among the latent factors in phase two of the analysis.

Model specification. The stage-two measurement model consisted of the six stage-one constructs – ITI, GOAL, EFFORT, FAIL, STRAT, and AA – and the new ASP construct. The measurement model for stage two incorporated 28 observed variables as effect indicators. Table 29 provides the Spearman correlation coefficients and two-tailed significance estimates of SC, SE15, and SC610 with the other measured variables in the model. Error covariances and reference factor loadings were replicated from the stage-one measurement model. In total, the stage-two measurement model specified the following: 28 path coefficients, 21 correlations between latent factors, 28 error variances for the effect indicators, and 15 error covariances between effect indictors.

Table 29

Spearman Correlation Coefficients and Significance (Two-tailed) for SC, SE15, and SE610

Variable	SC	SE15	SE610
ENT1	-.018[a] .691[b]	-.034 .443	-.058 .198
ENT2	.005 .911	-.052 .247	-.057 .200
ENT3	-.057 .202	-.014 .748	-.013 .776
PERF1	.021 .642	.010 .825	.011 .804
PERF2	-.095 .033	-.075 .096	-.105 .018
PERF3	.017 .699	.028 .538	.044 .322
PERF4	.153 .001	.056 .212	.128 .004
LEARN3	.163 .000	.101 .024	.097 .030
LEARN4	.176 .000	.024 .588	.116 .009
AVOID1	.079 .078	.027 .545	.109 .014
AVOID2	.094 .036	.078 .080	.127 .004

AVOID3	.154 .001	.143 .001	.136 .002
NEGEFF1	.118 .008	.189 .000	.156 .000
NEGEFF2	.117 .009	.156 .000	.100 .025
NEGEFF3	.102 .023	.070 .119	.072 .110
POSEFF1	.219 .000	.163 .000	.216 .000
POSEFF2	.067 .133	.037 .404	-.007 .880
POSEFF3	.096 .032	.067 .136	.064 .150
POSEFF4	.243 .000	.092 .040	.130 .003
EFFORT1	.015 .739	.117 .009	.037 .408
EFFORT2	.066 .137	.118 .008	.018 .681
POSSTAT1	.175 .000	.195 .000	.113 .011
POSSTAT2	.152 .001	.148 .001	.085 .056
NEGSTAT1	.168 .000	.155 .001	.053 .238
EOCG	-.069 .121	-.051 .259	-.066 .139
SC	---	.346 .000	.379 .000
SE15		---	.611 .000

Note. N = 501.

[a] Spearman correlation coefficient; [b] Significance (two-tailed).

Model identification and estimation. The stage-two measurement model specified 91 free parameters to be estimated among 28 observed variables. The number of distinct values in the sample data matrix composed of these 28 variables exceeded the number of parameters to be estimated. With no issues of empirical underidentification in the specification of the model, the measurement model was determined to be overidentified.

Figure 15 depicts the standardized parameter estimates of the stage-two measurement model and corresponding factor loadings, while Table 30 provides correlations among the latent factors for the model. Significant correlations between the latent factors ranged from .14 and .80, $p < .01$. Again, FAIL and STRAT demonstrated high collinearity, $r = .80$, however issues of multicollinearity remain non-threatening due to the ordering of causal relationships in the stage-two structural model. Most notably in the stage-two model, ASP was moderately correlated with EFFORT, $r = .30$, $p < .01$, and somewhat correlated with both GOAL, $r = .17$, $p < .01$, and STRAT, $r = .18$, $p < .01$. Table 31 provides the standardized parameter estimates for each effect indicator as well as reliability estimates for the indicator variables and overall constructs. Similar to the stage-one model, R^2 values for the effect indicators varied widely from .05 to .90, while each construct had at least one indicator with $R^2 \geq .30$ indicating moderate reliability. When compared to the stage-one measurement model, many of the same indicators replicated their high reliability in the stage-two measurement model. However, NEGEFF1 replaced POSEFF3 as the most reliable indicator for the EFFORT construct in the stage-two measurement model ($R^2 = .30$). The most reliable indicator for the ASP construct was SE610 ($R^2 = .68$). The demonstrated reliability of the entire measurement model remained exceptionally high, coefficient $H = .97$.

Model testing. By appending the ASP construct to the initial measurement model, the stage-two measurement model maintained acceptable goodness-of-fit to the sample population data. The absolute fit of the implied covariance in the measurement model fit the covariance present in the sample data, SRMR = .070. The comparison of the implied model to the null distribution also improved the noncentrallity of the data

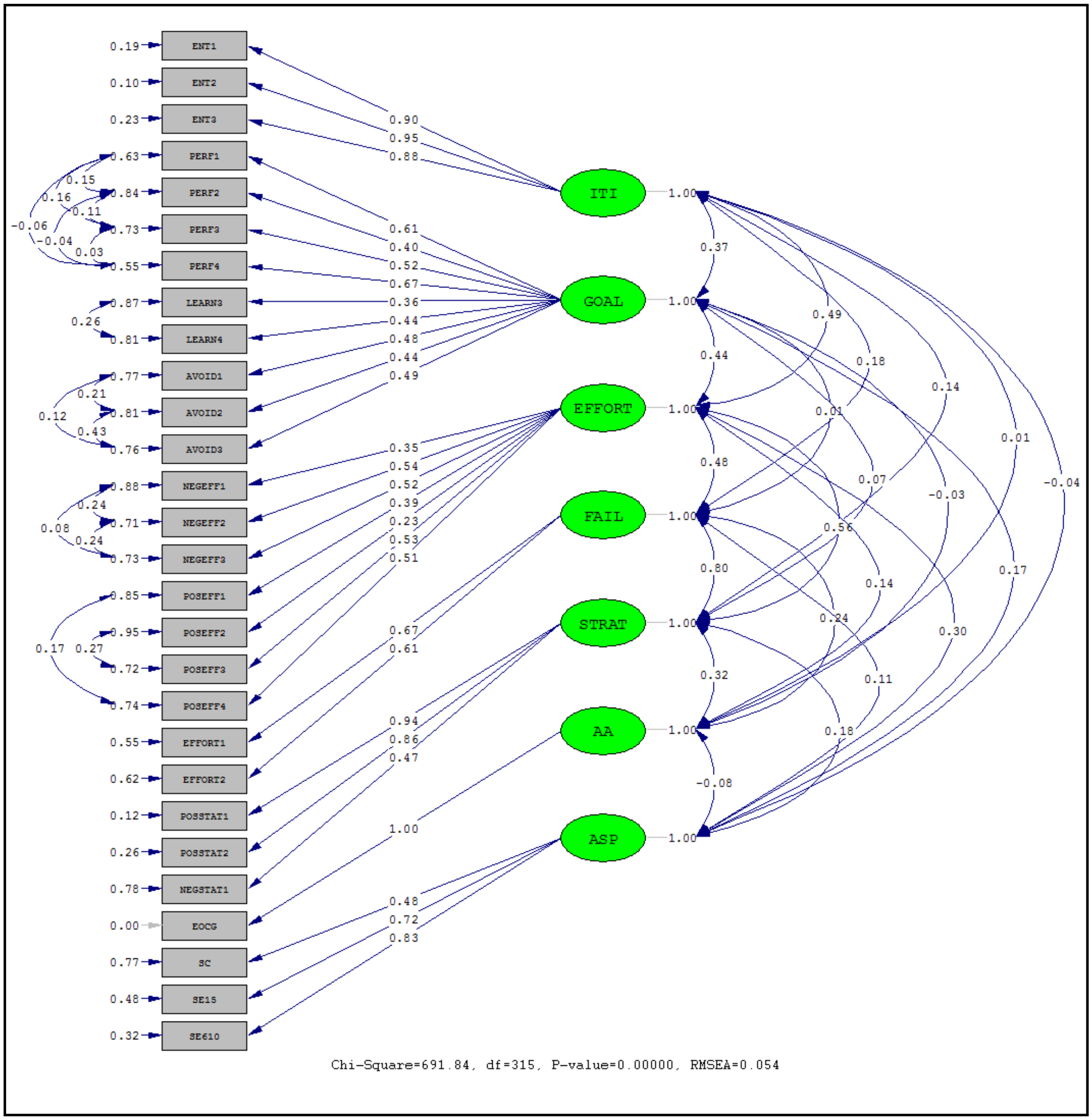

Figure 15. Standardized parameter estimates of stage-two measurement modeling for alternative hypothesis model including academic self-perception (N = 501). ITI = implicit theories of intelligence; GOAL = goal orientation; EFFORT = beliefs about the utility of effort; FAIL = failure attributions; STRAT = achievement strategies; AA = academic achievement; ASP = academic self-perception.

distribution, CFI = .950. Finally, the parsimony of the model was determined to have close fit, RMSEA = .054, 90% CI [.049, .059]. While the S-B scaled-χ^2 of 691.85 (*df* = 315) was significant at the .001 alpha level, the index was disregarded given the strength of the previous three indices. A review of the standardized residuals did not suggest overall specification error, and modification indices provided by LISREL failed to warrant changes that would conform to theory. Therefore, the initial stage-two measurement model was adopted as the final measurement model. Having demonstrated appropriate fit to the measured variance-covariance in the sample data, the stage-two measurement model was approved for structural analysis.

Table 30

Correlations and Standard Errors among Latent Factors for Stage-two Measurement Model

Variable	ITI	GOAL	EFFORT	FAIL	STRAT	AA
ITI	1.000					
GOAL	0.366** (0.048)	1.000				
EFFORT	0.493** (0.056)	0.444** (0.069)	1.000			
FAIL	0.179** (0.066)	0.006 (0.088)	0.479** (0.072)	1.000		
STRAT	0.144** (0.053)	0.067 (0.073)	0.558** (0.050)	0.802** (0.050)	1.000	
AA	0.006 (0.044)	-0.035 (0.059)	0.144** (0.055)	0.243** (0.069)	0.320** (0.049)	1.000
ASP	-0.038 (0.052)	0.172** (0.059)	0.304** (0.058)	0.114 (0.072)	0.179** (0.057)	-0.080 (0.052)

Note. *N* = 501. ITI = implicit theories of intelligence; GOAL = goal orientation; EFFORT = effort beliefs; FAIL = failure attribution; STRAT = academic strategies; AA = academic achievement; ASP = academic self-perception.

**p <.01, two-tailed.

Table 31

Standardized Factor Loadings and Reliability Estimates for Stage-two Measurement Model Constructs

Construct	Indicator Variables	Standardized Factor Loading	Error Variance	Indicator Reliability (R^2)	Coefficient *H*
ITI	ENT1	.90	.19	.81	.94
	ENT2	.95	.10	.90	
	ENT3	.88	.23	.77	
GOAL	PERF1	.61	.63	.37	.76
	PERF2	.40	.84	.16	
	PERF3	.52	.73	.27	
	PERF4	.67	.55	.45	
	LEARN3	.36	.87	.13	
	LEARN4	.44	.81	.19	
	AVOID1	.48	.77	.23	
	AVOID2	.44	.81	.19	
	AVOID3	.49	.76	.24	
EFFORT	NEGEFF1	.35	.88	.12	.66
	NEGEFF2	.54	.71	.30	
	NEGEFF3	.52	.73	.27	
	POSEFF1	.39	.85	.15	
	POSEFF2	.23	.95	.05	
	POSEFF3	.53	.72	.29	
	POSEFF4	.51	.74	.26	
FAIL	EFFORT1	.67	.55	.45	.58
	EFFORT2	.61	.62	.38	
STRAT	POSSTAT1	.94	.12	.88	.90
	POSSTAT2	.86	.26	.74	
	NEGSTAT1	.47	.78	.22	
AA	EOCG	1.00	.00	1.00	--
ASP	SC	.48	.77	.23	.78
	SE15	.72	.48	.52	
	SE610	.83	.32	.68	

Note. $N = 501$.

Stage Two: Structural Model Analysis

The second phase in stage two of this study sought to determine whether addition of the ASP construct significantly modified the theoretical relationships of Dweck's (1999) model. As stage one of this study was unable to validate Dweck's model as originally conceptualized, addition of the ASP construct would have to meet two criteria in order to be considered theoretically sound: (1) the overall model would have to meet all goodness-of-fit indices indicating the implied theoretical relationships were observed in the sample data, and (2) the stage-two model would have to be significantly different from the model tested in stage one as demonstrated by the S-B scaled difference test (or likelihood ratio test). To run this analysis, the hypothesized relationships between ASP and Dweck's (1999) motivational model of achievement were initially specified. As in stage one, model parameters were then identified, estimated, and tested according to relevant goodness-of-fit indices. The final structural model was then adopted based on an analysis of the estimated parameters' relative weights and goodness-of-fit. Finally, if the model demonstrated acceptable goodness-of-fit, it was compared to the final structural model of phase one according to the S-B scaled difference test.

Model specification. The structural model for stage two of this study nested Dweck's (1999) motivational model of achievement into a model that considered the moderating influence of ASP on various factors within Dweck's model. Therefore, the stage-two structural model specified all relationships in Dweck's theoretical model while simultaneously specifying three hypothesized relationships between ASP and factors in Dweck's model. The stage-two structural model suggested ASP exerts a direct influence on students' adopted goal orientations (GOAL), the strategies students employ in academic settings (STRAT), and their academic achievement (AA).

The stage-two structural model consisted of the seven latent factors and 28 effect indicators comprising the measurement model. The model also specified error covariances where recommended by prior factor analyses. As in previous analyses, the error variance of EOCG was set to zero. Reference variables also remained the same for the six original constructs, while SC served as the reference variable for the ASP construct. In total, the initial structural model for stage two specified the following: 10 structural equations composed of 10 structure coefficients and 10 disturbance terms, 2 exogenous variable variances, 21 path coefficients with 7 factor loadings fixed to one), 27 error variances for the effect indicators, and 15 error covariances between effect indicators.

Model identification and estimation. The initial stage-two structural model identified 80 parameters to be estimated. As was observed in the measurement model, the number of distinct variables in the sample data matrix for the structural model exceeded the number of parameter estimates. With no issues of empirical under-identification, the model was considered over-identified, allowing estimation of all parameters.

Robust maximum likelihood (ML) was again used to estimate the parameters of the stage-two structural model. The unstandardized parameter estimates for the stage-two structural model are provided in Figure 16. Tables 32, 33, and 34 provide the standardized ML estimates for the effect indicator factor loadings, specific covariances between measured variables, and structural relationships between the latent factors. Addition of the ASP construct and associated relationships did little to alter the factor loadings of the nested model: all estimated factor loadings remained significant at the .01 alpha level while those error covariances that were significant in the measurement model remained significant in the structural model.

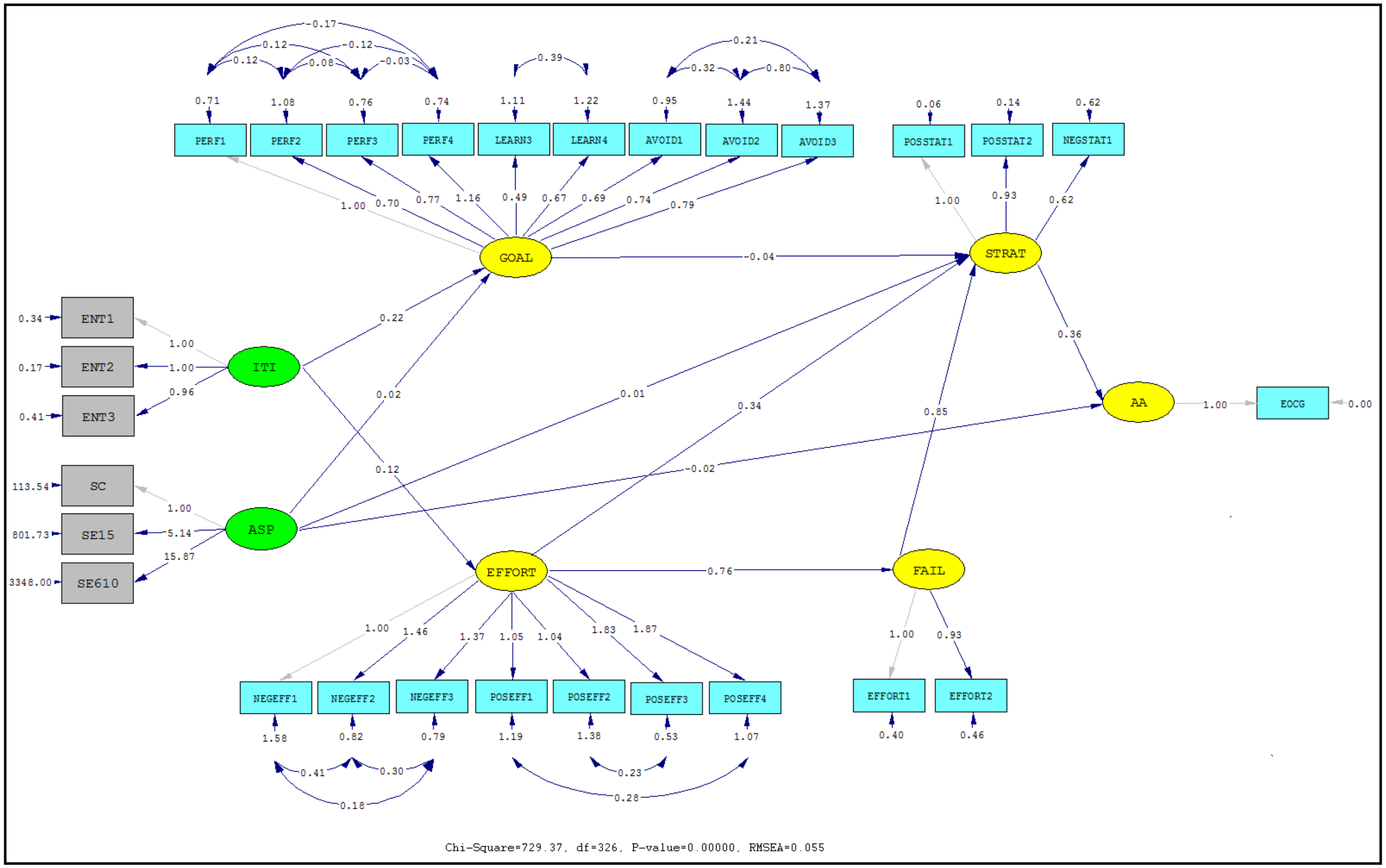

Figure 16. Unstandardized parameter estimates of stage-two structural modeling for initial alternative hypothesis model of achievement at the post-secondary level including academic self-perception (N = 501). ITI = implicit theories of intelligence; GOAL = goal orientation; EFFORT = beliefs about the utility of effort; FAIL = failure attributions; STRAT = achievement strategies; AA = academic achievement; ASP = academic self-perception.

Table 32

Factor Loadings and Reliability Estimates for Stage-two Structural Model Constructs

Construct	Indicator Variables	Standardized Factor Loading	Standardized Error Variance	Indicator Reliability (R^2)	Coefficient *H*
ITI	ENT1	.90**	.19	.81	.94
	ENT2	.95**	.11	.90	
	ENT3	.88**	.23	.77	
GOAL	PERF1	.66**	.51	.44	.78
	PERF2	.45**	.75	.20	
	PERF3	.58**	.66	.31	
	PERF4	.71**	.46	.50	
	LEARN3	.33**	.91	.11	
	LEARN4	.42**	.84	.17	
	AVOID1	.47**	.79	.22	
	AVOID2	.42**	.84	.18	
	AVOID3	.45**	.81	.21	
EFFORT	NEGEFF1	.27**	.92	.07	.68
	NEGEFF2	.49**	.76	.24	
	NEGEFF3	.48**	.77	.23	
	POSEFF1	.32**	.89	.10	
	POSEFF2	.30**	.91	.09	
	POSEFF3	.66**	.56	.44	
	POSEFF4	.54**	.71	.29	
FAIL	EFFORT1	.67**	.55	.45	.59
	EFFORT2	.62**	.62	.38	
STRAT	POSSTAT1	.94**	.12	.88	.91
	POSSTAT2	.86**	.26	.73	
	NEGSTAT1	.47**	.78	.22	
AA	EOCG	1.00	.00	1.00	
ASP	SC	.47**	.78	.22	.79
	SE15	.71**	.49	.51	
	SE610	.84**	.30	.70	

Note. $N = 501$.

**$p < .01$.

Table 33

Error Covariance Terms for Stage-two Structural Model

Variable	PERF1	PERF2	PERF3	LEARN3	AVOID1	AVOID2
PERF2	.116					
PERF3	.118	.077				
PERF4	-.172*	-.123	-.028			
LEARN4				.387**		
AVOID2					.322**	
AVOID3					.211**	.796**
Variable	NEGEFF1	NEGEFF2	POSEFF1	POSEFF2		
NEGEFF2	.409**					
NEGEFF3	.181**	.305**				
POSEFF3				.232**		
POSEFF4			.281**			

Note. *$p < .05$, two-tailed; **$p < .01$, two-tailed.

While LISREL 9.1 encountered no issues when estimating the structural coefficients for the specified relationships between latent factors, the relative weights and direction of some estimates were unexpected. Yet again, adoption of goal orientations did not play a significant role in the strategies students employ for academic success. ($\beta = -.04$, $p = .415$). Furthermore, the estimated model suggested students' academic self-perception had a slight yet significant negative influence on student achievement ($\beta = -.14$, $p = .007$). This is surprising given the hypothesis that the causal effect of ASP on AA would be positive. The effect of ASP on goal orientations ($\beta = .15$) and academic strategies ($\beta = .09$) were also smaller than anticipated yet significant at the .05 alpha level.

Similar to findings from stage one, the variance for each endogenous factor in the stage-two structural model was adequately explained by the regressed factors. Simultaneously accounting for ASP in addition to ITI accounted for 15 percent of the variance in GOAL ($R^2 = .15$), an increase of 3 percent over ITI alone. However, accounting for ASP did not improve the explained variance for STRAT ($R^2 = .67$).

Finally, accounting for ASP slightly improved the understanding of AA by 2 percent, whereby 12 percent of the variance in AA was explained by the combination of ASP and STRAT ((R^2 = .12) compared to 10 percent by STRAT alone in the stage-one model.

Table 34

Structural Relationships Between Latent Factors in Stage-two Model

	R^2	Path Coefficients						Error Variance
		ITI	GOAL	EFFORT	FAIL	STRAT	ASP	
GOAL								
B		0.223					.020	
t value	.15	6.598					2.832	.478**
p value		.000					.005	
β		0.36					.15	
EFFORT								
B		0.124						
t value	.18	3.981						.102*
p value		.000						
β		0.42						
FAIL								
B				0.760				
t value	.22			3.439				.251**
p value				.001				
β				0.47				
STRAT								
B			-0.037	0.339	0.848		.011	
t value	.67		-0.815	2.201	7.547		2.008	.151**
p value			.415	.028	.000		.045	
β			-0.04	0.18	0.72		.09	
AA								
B						0.358	-.018	
t value	.12					7.321	-2.699	.451**
p value						.000	.007	
β						0.34	-.14	

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

Model testing. While the addition of the ASP construct provided significant parameter estimates, tests of goodness-of-fit were again mixed. Close parsimonious fit was reached indicating each variable was making a useful contribution to the model, RMSEA = .055, CI 90% [.050, .060]. The parsimony index, however, was the only fit index to meet acceptable thresholds of goodness-of-fit. The incremental fit, whereby the implied covariance of the structural model was compared to the null distribution, did not meet acceptable thresholds for valid fit, CFI = .947. Similarly, the absolute fit of the implied covariance in the structural model on the covariance in the sample data was inadequate to suggest an overall tenable explanation of achievement motivation, SRMR = .083. The significant S-B scaled-χ^2 of 729.367, $df = 326$, $p < .001$ confirmed poor overall fit of the model. An inspection of the standardized residual covariance matrix and modification indices provided by LISREL did not reveal theoretically sound ways of improving the structural fit of the model to the data. Therefore, the initial model was adopted as the final model for stage two of the study. As specified, the final stage-two structural model produced an implied covariance between the factors that did not fit the covariance present in the sample data and could therefore not be recommended as an empirically sound model of motivation. Therefore, comparison of the stage-two model with the stage-one model was rendered moot.

Further inspection of the standardized residual covariance matrix revealed large standardized residuals similar to that of the stage-one structural model between the effect indicators of GOAL and the effect indicators for both EFFORT and STRAT (ranging from 2.661 to 5.843). The inability of the stage-two structural model to improve the incremental and absolute fit statistics of the nested model suggested that accounting for students' academic self-perceptions does not accommodate for the misspecification of student goal orientation and therefore cannot improve the causal explanation of motivation and achievement as specified by Dweck (1999) at the collegiate level. Having introduced an ASP factor to the original specifications of Dweck's conceptual model, the alternative hypothesis model did not meet acceptable thresholds for goodness-of-fit and likewise cannot serve as a tenable explanation of achievement motivation at the post-secondary level.

Stage Three: Modification of Original Model

While the addition of an academic self-perception factor did not increase the absolute fit of Dweck's (1999) hypothesized model, findings from stage one and stage two of the study seemed to indicate further modification of Dweck's hypothesis was warranted. Estimates of both the stage-one and stage-two hypothesized models revealed nonsignificant relationships between the goal orientation (GOAL) and achievement strategy (STRAT) constructs. As alluded to earlier in this chapter, these nonsignificant findings are reasonable given the discrepancies in the goal orientation literature at the collegiate level (reviewed in chapter two). Thus, it is plausible to suggest that among college students, mindsets may still influence achievement motivation; however, goal orientation may not play the same mediating role between mindsets and academic achievement as it does at the K-12 level.

In order to fully understand whether student mindsets play a significant role in the motivation and academic achievement of first- and second-year students enrolled in STEM courses at the collegiate level, the stage-one motivation model was modified to create the *modified model of mindsets and achievement motivation* (see Figure 17). The modified model of mindsets and achievement motivation excluded the goal orientation factor while preserving the other relationships specified in Dweck's (1999) model: instead of exerting influence on two constructs, implicit theories of intelligence (ITI) was hypothesized to exert influence only on effort beliefs (EFFORT); in turn, EFFORT influenced the adopted achievement strategies (STRAT) both directly and indirectly through the mediation of students' failure attributions (FAIL); finally, as in the previous models, academic strategies were assumed to directly influence students' academic achievement. Having removed the goal orientation construct, a phase-one measurement model was run to test the overall relationships between the remaining latent constructs. The structural relationships were then specified, and estimates were calculated using robust ML estimation. After testing the model's goodness-of-fit, the model was then compared to the original nested model using the S-B scaled difference test to determine whether the modified model was more theoretically sound than the model originally proposed by Dweck (1999) at the post-secondary level.

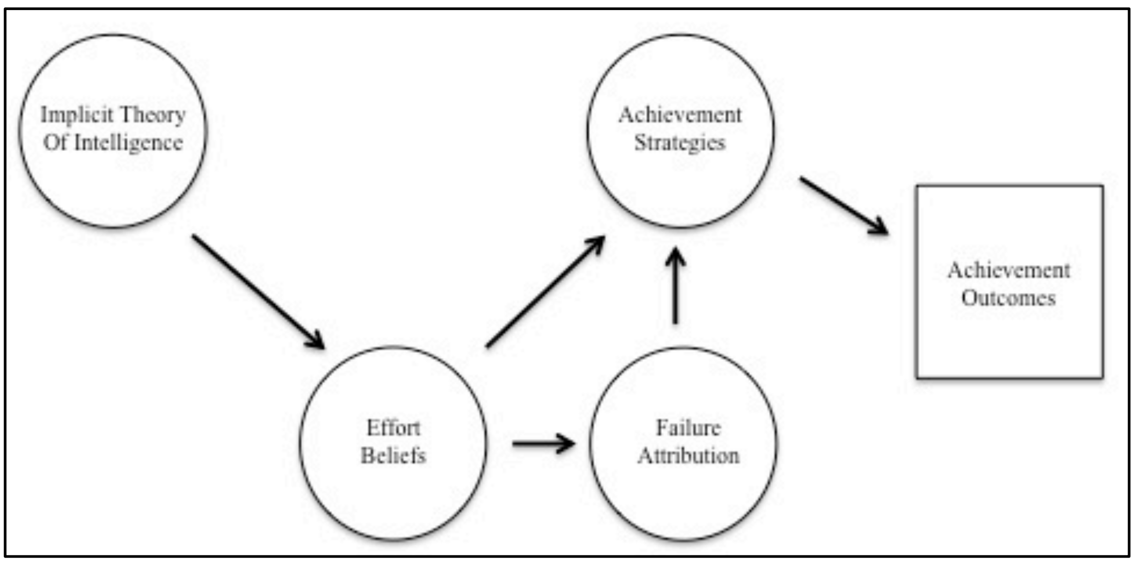

Figure 17. Modified model of mindsets and achievement motivation at the post-secondary level. Model specifies Dweck's (1999) hypothesized relationships between ITI, EFFORT, FAIL, STRAT, and ACHIEVE while excluding the goal orientation construct.

Phase One: Measurement Model Analysis

Model specification and model identification. The modified measurement model was composed of five latent constructs including implicit theories of intelligence

(ITI), effort beliefs (EFFORT), failure attribution (FAIL), achievement strategies (STRAT), and the endogenous outcome criterion of academic achievement (AA). Similar to the previous measurement models, effect indicator error terms were allowed to covary according to results from the CFA models. Again, the error term for EOCG was set to zero in effect standardizing the loading for the AA latent factor. In total, the measurement model specified 47 parameters to be estimated:16 path coefficients, 10 correlations between latent factors, 16 error variances for the effect indicators, and 5 error covariances between effect indicators. With 16 observed variables, the distinct values in the sample matrix exceeded the number of parameters to be estimated. With no issues of empirical underidentification present in the model, the model was considered overidentified and able to provide estimates for each parameter.

Model estimation and model testing. Figure 18 depicts the initial standardized parameter estimates and corresponding factor loadings for the modified model of mindsets and achievement motivation. Table 35 provides the correlations and standard errors among the latent factors for the model. Removal of the goal orientation construct did little to change the estimated parameters of the model, with significant correlations ranging from .15 and .80, $p < .01$.

Overall, the modified model of mindsets and achievement motivation measurement model demonstrated acceptable fit, suggesting the variance-covariance in the implied measurement model sufficiently reproduced the variance-covariance in the sample covariance matrix. The absolute fit of the model reached an adequate level and was better than both previous models, SRMR = .057. Similarly, the CFI index measuring the incremental fit of the model reached an acceptable level of .976. Finally, the

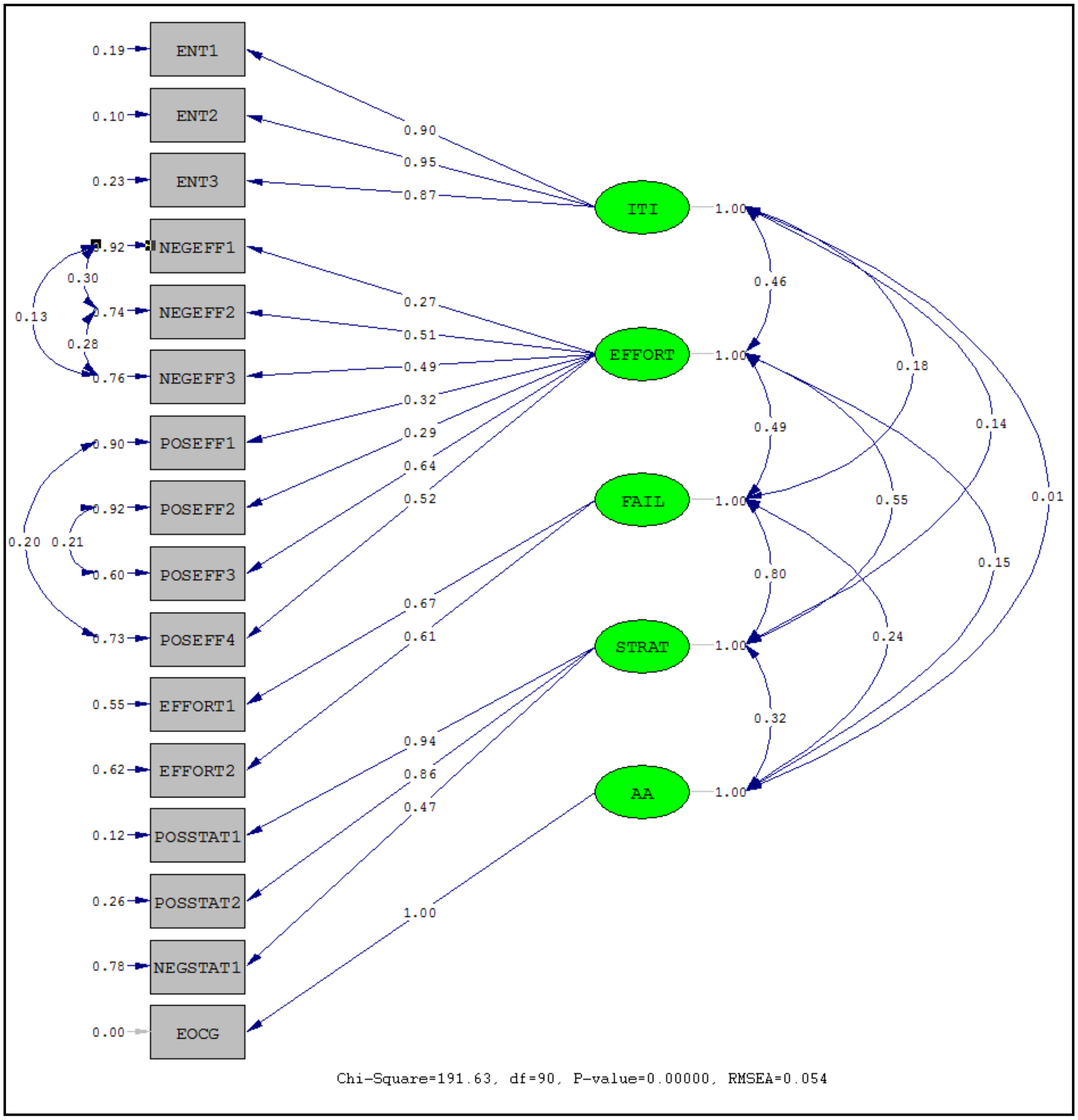

Figure 18. Standardized parameter estimates of modified model of mindsets and achievement motivation (N = 501). ITI = implicit theories of intelligence; EFFORT = beliefs about the utility of effort; FAIL = failure attributions; STRAT = achievement strategies; AA = academic achievement.

parsimony of the model was considered to be a good fit, RMSEA = .054, 90% CI [.044, 063]. Yet again, the S-B scaled-χ^2 of 191.63 (*df* = 90) was significant at the .05 alpha level, but was disregarded given the strength of the absolute, incremental, and parsimonious fit indices. Having appropriately specified the measurement variables for the modified model and tested the model's goodness-of-fit, it was determined that the structural modeling phase for the modified model could proceed.

Table 35

Correlations and Standard Errors among Latent Factors for Modified Model of Mindsets and Achievement Motivation Measurement Model

Variable	ITI	EFFORT	FAIL	STRAT	AA
ITI	1.000				
EFFORT	0.461** (0.055)	1.000			
FAIL	0.179** (0.066)	0.486** (0.073)	1.000		
STRAT	0.144** (0.053)	0.549** (0.052)	0.803** (0.050)	1.000	
AA	0.006 (0.044)	0.150** (0.055)	0.243** (0.069)	0.320** (0.049)	1.000

Note. *N* = 501. ITI = implicit theories of intelligence; EFFORT = effort beliefs; FAIL = failure attribution; STRAT = academic strategies; AA = academic achievement.
***p* <.01, two-tailed.

Phase Two: Structural Model Analysis

Model specification. The structural relationships of the modified model were specified as previously described. Covariances between effect error terms were also preserved from the nested model: these included covariances between the negative valence EFFORT items error terms, the error terms of POSEFF2 and POSEFF3, and the error terms of POSEFF1 and POSEFF4. The reference variables identified in stage one were also used for each construct in the modified model. Similarly, the error variance for

EOCG was again set to zero. In total, the modified model specified 5 structural equations composed of 5 structural coefficients and 5 disturbance terms, 1 exogenous variable variance, 11 path coefficients (with 5 factor loadings fixed to one), 16 error variances for the effect indicators, and 5 error covariances between effect indicators.

Model estimation. Estimates for the specified parameters of the modified model were calculated using robust maximum likelihood (ML) in LIRSEL 9.1 (Jöreskog & Sorböm, 2013). Figure 19 provides the unstandardized parameter estimates for the modified model, while Tables 36, 37, and 38 provide the standardized ML estimates for the measured variables, specified covariances between measured variables, and structural relationships between all latent factors. For the most part, estimates resembled those of the parameter estimates from the stage-one model. All factor loadings, structural coefficients, error variances and covariances were significant at the .01 alpha level. Similarly, the relative magnitude and direction for all parameter estimates seemed to conform to *a priori* theory. As in the nested model, incremental implicit theories of intelligence had a positive influence on students' beliefs about the utility of effort (β = .41). Beliefs about effort significantly influenced how students attribute causes to failure (β = .47) and their choice of positive achievement strategies (β = .52), both through a direct effect (β = .18) and mediated by failure attributions (β = .34). Students' attribution of lack of effort to failure had a direct effect on their choice of positive achievement strategies (β = .72). Positive achievement strategies accounted for increases in student academic achievement (β = .32). Finally, the model suggested that a growth mindset had a significant and positive total effect on students' end-of-course exams (β = .07).

Similarly, the variance for the endogenous factors did not change with removal of the goal orientation construct. Most notably, EFFORT and FAIL accounted for 67 percent of the variance in the achievement strategies construct (R^2 = .67) while STRAT accounted for 10 percent of the variance in academic achievement (R^2 = .10). These calculated R^2s are identical to those in the stage-one structural model that included the goal orientation predictor. These values further support the hypothesis that goal orientation played no significant role in the efficacy of the model.

Model Testing. Appropriate tests of absolute, incremental, and parsimonious fit each met acceptable thresholds to suggest the implied covariance of the model fit the covariance measured in the sample data. The absolute fit of the implied covariance in the model was improved over the nested model, SRMR = .060. Similarly, the model improved the incremental fit, whereby the implied covariance of the structural model improved the noncentral distribution of the data when compared to the null distribution, CFI = .975. Finally, it was concluded that each variable was making useful contributions to the model indicating good parsimony, RMSEA = .053, 90% CI [.044, .061]. While the S-B scaled-χ^2 was significant at 197.514, df = 95, $p < .001$, this index was disregarded given its propensity to detect trivial fluctuations in the data. Having met acceptable thresholds for each goodness-of-fit index, the model was adopted as an appropriate measure of motivation that could be compared to the nested model in stage one.

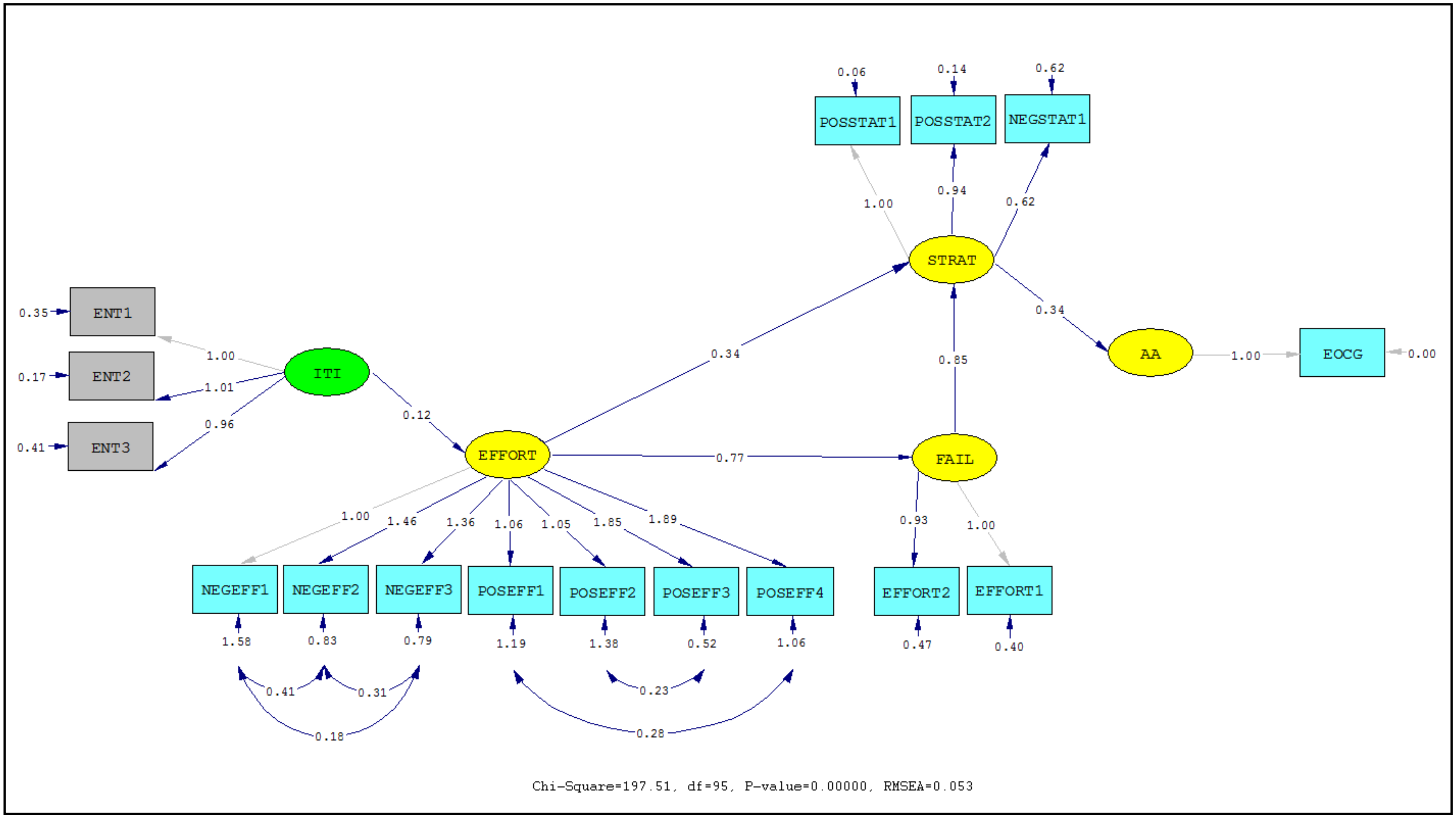

Figure 19. Unstandardized parameter estimates of structural modeling for modified model of mindsets and achievement motivation at the post-secondary level (N = 501). ITI = implicit theories of intelligence; EFFORT = beliefs about the utility of effort; FAIL = failure attributions; STRAT = achievement strategies; AA = academic achievement; ASP = academic self-perception.

Table 36

Factor Loadings and Reliability Estimates for Modified Structural Model Constructs

Construct	Indicator Variables	Standardized Factor Loading	Standardized Error Variance	Indicator Reliability (R^2)	Coefficient *H*
ITI	ENT1	.90**	.19	.81	.94
	ENT2	.95**	.10	.90	
	ENT3	.88**	.23	.77	
EFFORT	NEGEFF1	.27**	.93	.07	.68
	NEGEFF2	.49**	.76	.24	
	NEGEFF3	.47**	.78	.22	
	POSEFF1	.32**	.90	.10	
	POSEFF2	.30**	.91	.09	
	POSEFF3	.67**	.55	.45	
	POSEFF4	.54**	.71	.29	
FAIL	EFFORT1	.67**	.55	.45	.58
	EFFORT2	.61**	.62	.38	
STRAT	POSSTAT1	.94**	.12	.88	.91
	POSSTAT2	.86**	.26	.74	
	NEGSTAT1	.47**	.78	.22	
AA	EOCG	1.00	.00	1.00	

Note. $N = 501$.

**$p < .01$.

Table 37

Error Covariance Terms for Modified Structural Model

Variable	NEGEFF1	NEGEFF2	POSEFF1	POSEFF2
NEGEFF2	.411**			
NEGEFF3	.184**	.308**		
POSEFF3				.227**
POSEFF4			.279**	

Note. *$p < .05$, two-tailed; **$p < .01$, two-tailed.

Model Comparison

In order to determine whether the modified model is significantly different from Dweck's (1999) hypothesized model and therefore an improved alternative, a S-B scaled difference test was conducted. The S-B scaled difference test emulates a likelihood ratio (LR) test, whereby the χ^2 statistics for each model are compared. As estimation of the

Table 38

Structural Relationships Between Latent Factors in Modified Model

	R^2	Path Coefficients				Error Variance
		ITI	EFFORT	FAIL	STRAT	
EFFORT						
B		0.120				
t value	.18	3.931				.102*
p value		.000				
β		0.41				
FAIL						
B			0.767			
t value	.22		3.433			.222**
p value			.001			
β			0.47			
STRAT						
B			0.342	0.850		
t value	.67		2.220	7.629		.151**
p value			.026	.00		
β			0.18	0.72		
AA						
B					0.337	
t value	.10				6.722	.461**
p value					.00	
β					0.32	

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

models required a scaling correction factor (c) to account for the nonnormality in the data, the S-B scaled difference test was employed instead of a tradition LR test to account for the scaling difference. First, c was calculated by dividing the NTWLS χ^2 statistic of the modified model provided by LISREL 9.1 by the S-B scaled-χ^2 statistic of the modified model. For the nested models, $c = 1.151$. The NTWLS χ^2 statistic for the modified model was then subtracted from the NTWLS χ^2 statistic for the stage-one model, NTWLS χ^2 difference = 396.555. This value was then divided by c to calculate the S-B scaled difference χ^2 of 344.531. The difference in degrees of freedom between the nested models was 159. Therefore, the S-B scaled difference test suggests that with a

S-B scaled difference χ^2 of 344.531, *df* = 159, the modified model is significantly different from the nested model at .001 alpha level.

In order to determine the power of the S-B scaled difference test statistic, the effect size (δ) was first calculated by comparing the degrees of freedom and parsimony in the model according to MacCallum et al. (2006), where $\delta = df_{nested} \times RMSEA_{nested} - df_{modified} \times RMSEA_{modified}$. The effect size was calculated as (254 x .054) – (95 x .053) = 8.681. Next, the noncentrallity parameter (NCP) was calculated by multiplying δ by *N*-1, NCP = 4,340.50. The NCP, sample size, and degrees of freedom were then used to calculate the power of detecting differences in the structure of the comparative models using G*Power 3 (Buchern et al., 2014). G*Power calculated the ability to detect the difference between the comparative models at the .01 alpha level and obtained power = 1.00.

In light of these analyses, it was determined that the modified model (see Figure 19) was the most appropriate model for demonstrating the tenable causal relationships between implicit theories of intelligence, motivation, and achievement outcomes among college students. The modified model of mindsets and achievement motivation met thresholds for all goodness-of-fit indices, provided improved goodness-of-fit test statistics when compared to the original stage-one hypothesis model, and was significantly different from the original model. It was determined that addition of an academic self-perception factor did not add to the explanation of motivation and achievement according to mindsets theory; however, removal of the goal orientation construct resulted in a sound structural model.

CHAPTER 5

DISCUSSION

To highlight the contributions made by this study towards the understanding of how college students operationalize mindsets (i.e., implicit theories of intelligence) as part of an intrapersonal framework of achievement motivation, this chapter provides an overview of the research performed and summary of findings. These findings (detailed in chapter four) are discussed as they pertain to the original research questions of the study and as they relate to the individual constructs measured in the models. This chapter considers the limitations of the study and the significance of the findings in light of the relevant body of literature. Finally, this chapter provides a discussion of the implications for practice and suggestions for future research.

Overview of Research

While faculty at the collegiate level continue to alter their pedagogical approaches in order to provide support for learning as part of a learner-centered paradigm (and away from an instruction-centered paradigm that relies on traditional forms of lecture), the responsibility for achievement in the higher education classroom shifts from the instructor to the student (Barr & Tagg, 1995; Tagg, 2003). It is therefore of the utmost importance that educators understand what factors play a role in student achievement in this new paradigm. Contemporary efforts to understand this phenomenon have almost exclusively focused on how classroom environments affect student achievement and have failed to take into account the psychosocial effects of student motivation. This study sought to provide such insight by investigating how students' intrapersonal motivation can affect academic achievement at the post-secondary level.

Dweck's (1999) conceptual model of achievement motivation suggests that mindsets – or students' implicit beliefs in the malleability of intelligence – particularly influence motivation and achievement in academic domains. Her hypothesized model has received a great deal of attention over the last two decades, and for good reason. Past research suggests that growth and fixed mindsets serve as the antecedent for divergent motivational patterns (Dweck & Leggett; 1988; Hong et al., 1999; Robins & Pals, 2002) and can positively or negatively impact academic achievement both at the K-12 level (Blackwell et al., 2007) and post-secondary level (Aronson et al., 2002; Grant & Dweck, 2003). These studies, and others like them, have helped form a theoretical model of achievement motivation (see Figures 1 and 2) that has been successfully tested at the K-12 level (Blackwell et al., 2007). The model suggests that mindsets indirectly influence achievement outcomes by directly shaping students' goal orientation (Dweck & Leggett, 1988; Grant & Dweck, 2003) and beliefs in the utility of effort (Aronson et al., 2002; Hong et al., 1999), while indirectly influencing the ways students attribute failure to a lack of effort rather than ability (Henderson & Dweck, 1990; Stipek & Gralinski, 1996) and the academic strategies they adopt (e.g., Dweck & Sorich, 1999). Many of the relationships that undergird the motivational model of achievement have been explored at the post-secondary level, but prior research has not sought to test the full model with a sample comprised of college students. The present research undertook this task, and results of these findings are summarized below. The overarching research questions, hypotheses, and corresponding key findings are provided in Table 39.

Overall, this research provides a tenable explication of the relationship between mindsets and motivation for STEM students at the post-secondary level. Findings from the study suggest that STEM students who embody growth mindsets do realize higher academic achievement outcomes, and relationships were found between their mindsets and their intrapersonal motivation: students who believe in the malleability of intelligence receive higher end-of-course grades in introductory STEM courses than those who believe intelligence is fixed. However, the relationship between mindsets and achievement in this study does not fully conform to Dweck's (1999) motivational model of achievement. The analysis suggests that growth mindsets frame a positive motivational approach to learning through the adoption of mastery goal orientations, belief in the utility rather than the futility of effort, the ascription effort-based attributions to failure scenarios, and adoption of positive, mastery-oriented achievement strategies. Yet contrary to Dweck's hypotheses, the analysis also suggests that the goal orientations students endorse do not share a relationship with the achievement strategies they adopt in collegiate level STEM courses. Thus, I recommend that, in order to illustrate the true causal relationships between implicit theories of intelligence and academic achievement at the post-secondary level, the use of an alternative model excluding the influence of goal orientation (see Figure 17) may be more appropriate than Dweck's (1999) motivational model of achievement.

Table 39

Research Questions, Hypotheses, and Key Findings

Research Question	Key Findings
1. Do mindsets (i.e. students' implicit theories of intelligence) play a significant role in the motivation and academic achievement of first- and second-year students enrolled in STEM courses at the collegiate level? H_{01} = Mindsets will play a significant role in the motivation and academic achievement of first- and second-year students enrolled in STEM courses at the collegiate level.	• The sample data does conform to a modified model of mindsets and achievement motivation that excludes goal orientation yet preserves the remaining theoretical relationships from Dweck's (1999) model, suggesting implicit theories of intelligence do play a significant role in motivation and academic achievement. The data suggests implicit theories of intelligence directly influence beliefs about the utility of effort. Students adopt achievement strategies as a direct result of these effort beliefs and as an indirect result of the influence effort beliefs have on students' propensity to attribute effort (or ability) to failure. Finally, the strategies students adopt directly influence their academic achievement outcomes. • The modified model of mindsets and achievement motivation was determined to be an improved alternative to Dweck's hypothesized model according to a significant S-B scaled difference test.
2. If mindsets play a significant role in the motivation and academic achievement at the post-secondary level, do the relationships conform to the specified parameters proposed by Dweck's (1999) motivational model of achievement? H_{02} = Dweck's specifications will exhibit ill-defined fit among post-secondary students given the limitations expressed in prior research that suggest goal-orientation is a poor mediator of the relationship between mindsets and achievement strategies.	• The covariance in the sample data does not conform to the theoretical relationships proposed by Dweck's motivational model of achievement, suggesting implicit theories of intelligence do not affect achievement outcomes as originally specified. • When Dweck's theoretical relationships are modeled, an insignificant relationship between goal orientation and achievement strategies, coupled with high standardized residual covariances, suggest goal orientation is a spurious factor; it does not mediate the influence of implicit theories of intelligence on achievement strategies or achievement outcomes.

3. Does the addition of an academic self-perception factor (a higher-order factor encompassing domain-specific measures of self-concept and self-efficacy) add to the explanatory power of Dweck's theory, using a sample of first- and second-year college students enrolled in STEM courses? H_{03} = The introduction of an academic self-perception construct will add to the causal explanation of motivation and achievement while increasing the absolute model fit of Dweck's (1999) motivational model of achievement. When introduced to the proposed model, academic self-perception will account for the discrepant relationship between mindset and goal formation.	• Estimates of the theoretical relationships between the academic self-perception factors and corresponding factors in the model were significant. However, the fit of the sample data to the theoretical relationships of the model as a whole were unacceptable, most likely due to the misspecification of the goal orientation factor. • Addition of the academic self-perception construct did not sufficiently improve the absolute validity of the model to a point where the model could be considered empirically sound. • The revelation of significant causal relationships between academic self-perception and other factors in the model could not be validated in light of the unacceptable model fit. • As the goal orientation factor was determined to be spurious, moderating the goal orientation factor through inclusion of an academic self-perception becomes moot.

Interpretation of Findings

What role do mindsets play in the intrapersonal motivation and achievement of students at the collegiate level? The modified model of mindsets and achievement motivation developed by this study, coupled with the inability to either validate Dweck's (1999) motivational model of achievement as originally specified or accept an alternative model that includes academic self-perceptions, provides insight into this complex psychological framework. In particular, growth mindsets influence positive aspects of motivation that contribute to increases in academic achievement. However, the relationship between growth mindsets and high achievement does not seem to be mediated by the incremental theorist's tendency to adopt mastery goal orientations.

Latent variable path analyses were conducted in an effort to validate Dweck's (1999) motivational model of achievement in its entirety at the post-secondary level: an effort that was the first of its kind. However, the present research was unable to provide sufficient evidence to suggest this framework operates in the same way for first and second year students at a highly selective, public, research-intensive institution of higher education. The inability to validate the theory as originally specified might suggest that particular factors within the conceptual framework do not operate in the same way as they might at the K-12 level. Most notably, the data revealed that students' goal orientation seems to have no significant effect on those achievement strategies students tend to adopt, a relationship that does exist at the K-12 level and plays an important role in the mediation effects of implicit theories of intelligence on achievement for those students. While in keeping with findings that previously have sought to assess the relationship between mindsets, goal orientations, and achievement strategies at the post-secondary level (e.g., Dupeyrat & Marine, 2005), this finding is surprising given the larger narrative of the influential role goal orientation plays in the achievement motivation literature. A further consideration of this finding is discussed later in this chapter.

Dweck's (1999) original model aside, this study was able to provide a modified model of mindsets and achievement motivation that serves as a tenable demonstration of how growth mindsets increase motivation and promote increased achievement outcomes at the post-secondary level. According to the analysis, an increase of one standard deviation along the mindset spectrum from a fixed mindset to a growth mindset influences a .07 standard deviation increase of a student's end-of-course grade in an introductory STEM course. This finding is notable given the relative simplicity of the mindset concept: those who believe intelligence is malleable have a better chance of receiving a higher end-of-course grade than those who believe intelligence is a fixed entity.

Other studies have been able to demonstrate correlated relationships between mindsets and achievement without testing the full mediation model. In a pretest-posttest control group experimental design study, Aronson and his colleagues (2002) found that students who were conditioned to hold growth mindsets were more likely to earn higher GPAs than students conditioned to hold fixed mindsets or students serving as a control. Good, Aronson, and Inzlitch (2003) reported similar findings a year later from a population of junior high school students. They found that students in math courses from underperforming populations (racial minorities and women) were able to erase the achievement gap that had previously existed after participating in interventions that promoted growth mindsets.

But why would a belief in the malleability of intelligence affect achievement outcomes such as end-of-course grades? After all, is not a *belief* that intelligence can change qualitatively different than intelligence itself? A contemporary understanding of intelligence defines the construct as the ability to acquire and process knowledge, problem-solve, and reason (Sternberg, 1996). While the debate considering whether intelligence is malleable or fixed is on-going (see Barsalou, 2010), Dweck (1999; 2006) has argued that one's belief in the malleability of intelligence plays an important role in student motivation irrespective of the true nature of intelligence. According to Dweck, this is accomplished through the unique motivational characteristics aroused by one's mindset. If students believe their intelligence can change, they are more likely to apply effort to a given achievement opportunity (Hong et al., 1999). These incremental theorists, when faced with difficult achievement opportunities, believe that failure is most likely due to a lack of effort rather than ability (Henderson & Dweck, 1990). Consequently, students with a growth mindset are resilient (Dweck, 2006) and will seek to exert more effort when presented with similar opportunities (Henderson & Dweck, 1990; Dweck & Sorich, 1999). They are less likely to cast blame on their ability or give up as the difficulty increases (Hong et al., 1999; Nussbaum & Dweck, 2008). Finally, students with growth mindsets tend to practice achievement strategies that are motivated by mastery (e.g., studying, time-management) rather than helpless response patterns (e.g., procrastination, absenteeism) (Dweck & Sorich, 1999; Robins & Pals, 2002).

Achievement Motivation

The present study was able to provide a tenable explanation for how implicit theories of intelligence influence achievement motivation; this influence is accomplished, in part, through the impact of mindsets on students' understanding of effort and consequent adoption of achievement strategies. According to the LVPA analysis, the calculated parameter estimates suggest that growth mindsets directly influence students' beliefs in the utility of effort ($\beta = .41$) and, when faced with failure, indirectly trigger students' attributions of failure to a lack of effort rather than a lack of ability ($\beta = .19$). Beliefs in the utility of effort and propensity to attribute a lack of effort to negative performance has a combined total effect of increasing students' adoption of mastery-oriented achievement strategies by more than half of one standard deviation ($\beta = .52$).

The utility of effort. Students with growth and fixed mindsets view effort in a contrasting light. Students who embody a growth mindset focus on effort and seek to apply it as a tool for learning and growth (Dweck, 1999). When presented with opportunities for growth or challenging situations that outpace their present potential, students with a growth mindset seek to cultivate their abilities through applied effort (Hong et al., 1999). In comparison, students with a fixed mindset seek to prove their ability rather than grow it. This posture is akin to viewing effort as a sign of weakness or lack of ability (Dweck & Bempechat, 1983). Previous studies have demonstrated such effects. Hong and her colleagues (1999) found that student engagement in remedial coursework varied based upon their implicit theory of intelligence: students with a growth mindset were far more likely to enroll in a remedial class than those with a fixed mindset, even when the students knew the course was integral to their success.

The study was able to demonstrate a moderate effect size on the influence of implicit theories of intelligence on beliefs about the utility of effort. Results from the confirmed model suggest 17.2 percent of students' beliefs in the utility of effort are based on having a growth mindset. These beliefs were indicated by agreement with statements such as "if you don't work hard and put in a lot of effort, you probably won't do well," and disagreement with items similar to "if you're not good at a subject, working hard won't make you good at it" (from the *Effort Orientation Inventory,* Dweck & Sorich, 1999). Considering the students and the courses that composed the sampling frame of this study, these findings seem logical. Many of these introductory STEM courses are designed for rigorous study and serve as gateways to highly selective STEM degrees. The challenging nature of introductory STEM courses provides an environment where success is important and opportunities for students to implicitly apply their beliefs concerning effort (Grant & Dweck, 2003). The data from this study suggests that students with a growth mindset have a distinct advantage in these environments given the influence of their mindset on their propensity to apply effort in these situations.

Failure attributions and achievement strategies. Similarly, mindsets affect how students react to negative performance or failure. Hong and her colleagues (1999) suggest "although both entity and incremental theorists may see ability and effort as relevant causes of performance, the implicit theory they hold may orient them to assign unequal weights to these causes" (p. 589). When students believe effort is useful for learning and success, they tend to believe that negative performance results from a lack of effort. Entity theorists adopt different attributions for failure: because students with a fixed mindset focus on their ability, they often believe failure is an indicator of inadequate ability. Nussbaum and Dweck (2008) witnessed this tendency first hand in a study of undergraduates and the relationship between their mindsets and failure attributions. The participants in this study were asked to complete a speed-reading task designed to be difficult. After completing the task, each student was informed that they scored in the 37th percentile. They were then given the opportunity to look at how other students performed on the task. Consistent with the above theory, incremental theorists chose to look at the work of those that had performed well to see how their work was accomplished, while entity theorists chose to review the work of lesser performers, ostensibly validating their ability rather than seeking to improve their outcomes.

The modified model of mindsets and achievement motivation presented in this study demonstrates similar relationships. The model suggests that growth mindsets indirectly affect how students attribute the concept of effort to a failure scenario through mediation of their effort beliefs. Beliefs in the utility of effort had a sizable effect on students' attributing lack of effort to the provided failure scenario ($\beta = .47$), accounting for 22.2 percent of these beliefs. The importance of this factor in the achievement motivation theory is paramount, particularly given the nature of STEM coursework at the post-secondary level. Many of these courses have been designed to "weed out" students who are unable to apply the effort needed in order to succeed at a high level. A common perception that most students enrolled in organic chemistry courses will inevitably receive low grades is pervasive across the world of higher education. Yet according to the present research, the belief that failure results from a lack of applied effort rather than a lack of ability influences students' decisions to select mastery-oriented achievement strategies (as opposed to helpless response patterns) ($\beta = .72$). In fact, students' conceptions about the nature of effort (both the utility of effort and effort attributions for failure) account for 66.7 percent of students' decisions to choose either mastery-oriented strategies or helpless response patterns. Thus, incremental theorists enrolled in challenging STEM courses are more likely to believe that their applied effort will help them succeed in the face of these difficult classes and are more likely to apply mastery-oriented strategies to achieve these results. Entity theorists, on the other hand, are more likely to rely on their own ability, and should they experience failure, believe the failure is attributed to their inability to succeed. These beliefs, in turn, encourage students with fixed mindsets to hedge their outcomes by adopting helpless response patterns that allow students to attribute potential failure to external or unstable factors.

There is a great deal of literature that demonstrates the important ties between mastery-oriented strategies such as self-regulation and achievement outcomes (see Pascarella & Terenzini, 2005; Zimmerman & Schunk, 2001). The present study provides a tenable causal link between the two, suggesting that adoption of effort-based achievement strategies leads to gains in academic achievement, particularly end-of-course grades. According to the modified model of mindsets and achievement motivation, the tendency to adopt mastery-oriented achievement strategies affects a positive gain in students' end-of-course grades ($\beta = .32$). The moderate effect ($r^2 = .10$) of achievement strategies on achievement outcomes provides a clear rationale for 10 percent of the variance in students' end-of-course grades. As students are continually encouraged to apply more effort or embrace mastery-oriented achievement strategies, this study demonstrates that students' beliefs about the malleability of intelligence can have a profound effect on these factors that ultimately lead to increased performance.

Goal Orientation

The inability to endorse a model of achievement motivation that takes into account goal orientation stands out as an important finding from this study. The mediating role goal orientation plays in Dweck's (1999) motivational model of achievement has remained a central tenant of the theory over the course of nearly two decades and countless studies on the topic (see Dweck, 2006; Dweck & Master, 2009). Essentially, Dweck's (1999) theory proposes that a growth mindset instills a desire for mastery (or learning), while a fixed mindset promotes performance. Students adopt learning or performance goals according to their mindset, and in turn adopt achievement strategies that correspond these goals. Thus, learning-oriented students will adopt mastery-oriented strategies, while performance-oriented students will adopt helpless response patterns. This theory holds up well at the K-12 level, with a number of studies demonstrating these relationships (Blackwell et al., 2007; Dweck & Leggett, 1988; Farrell & Dweck, 1985). Hong and her colleagues (1999) were also able to demonstrate a link between mindsets, goal orientation, and achievement strategies at the post-secondary level. However, a number of studies have been unable to replicate these findings among college students (Dupeyrat & Marine, 2001; Dupeyrat & Marine, 2005; Stipek & Gralinski, 1996). Given the conflicting findings regarding the efficacy of goal orientation in a framework of mindset and achievement motivation, one wonder's whether college students adopt different goal orientations as a result of their mindsets and whether goal orientations influence the academic strategies students employ at the post-secondary level.

The ability to interpret the relationship between these factors according to the conducted analyses is murky at best. Because the sample covariance matrix was not sufficiently reproduced by Dweck's (1999) implied theoretical model, strict interpretations of the parameter estimates measured in the stage-one model are not empirically justified. However, the SRMR index measuring the absolute fit of the stage-one model was only slightly higher than the theoretically sound threshold of .080 (SRMR of stage-one model = .082). Noting these limitations, estimation of model parameters for the stage-one model revealed a significant relationship between student mindsets and goal orientations ($\beta = .22$, $p = .00$), whereby growth mindsets lead to the adoption of mastery (or learning) goals. This suggests that students enrolled in STEM courses at the post-secondary level rely on their beliefs about the malleability of intelligence to select and form their academic goals. And yet, how students are motivated by their goal orientations remain a mystery. Analysis of the data from the present study suggests that the goal orientation construct shares little common variance with the achievement strategies construct. The model would therefore suggest that the differentiation of mastery and performance goals has no bearing on student motivation in the STEM classroom.

Why does goal formation not play a significant role in the motivation of college students at the collegiate level? Theoretically, first- and second-year students who are enrolled in introductory STEM courses may not base their choice of achievement strategies on their implicit goal orientations. Akin to Dupeyrat and Marine (2005) who, in their study of 76 students where the majority were between 20 and 30 years old, found that performance goals were significantly linked to both shallow and deep learning strategies, results from the stage-one path model suggest that students do not differentiate their achievement strategies based on contrasting goal orientations. Put simply, both populations of college students – those seeking to learn and those seeking to perform – might adopt similar achievement strategies to meet their goals. In difficult or high-stake situations such as “gateway” STEM courses, it may be assumed that both types of students are seeking the same goal: to succeed. Thus, mastery-oriented and performance-oriented students could adopt achievement strategies that meet this shared need. The differentiation, therefore, is not based on goal orientation but rather the students’ understanding of effort, a construct that already accounts for 66.7% of the variance in achievement strategies.

It is possible that goal orientation continues to play an important role in achievement motivation, just not as according to the learning/performance framework proposed by Dweck (1999). As part of his task ego involvement model of goal orientation, Nichols (1984; 1989) suggested that task orientations (i.e, adoption of learning goals) and ego orientations (i.e., adoption of performance goals) are orthogonal constructs. Therefore, it is possible that students can independently endorse learning goals and performance goals simultaneously. For instance, pre-medical undergraduates enrolled in introductory chemistry classes might desire to increase their understanding of the concepts taught in the course while simultaneously seeking to demonstrate their superior ability given the highly-selective application process for medical schools. Nichols (1989) argued that students are likely to be highly motivated if they demonstrate high levels in one or both of these constructs. However, if students fail to demonstrate high levels of both task and ego involvement, these students are most likely to be unmotivated and therefore unsuccessful in achieving positive outcomes. Therefore, rather than comparing learning and performance goals to predict the adoption of mastery-oriented achievement strategies, a more appropriate method of analysis might explore the degree to which student mindsets influence the adoption of strong learning or performance goals.

Another explanation for the insignificance between goal orientation and achievement strategies could be derived from the type of goal orientations that were measured by the PALS goal orientation scale (Midgley et al., 1998). The scale measures students' goal orientations related to learning, performance, and performance avoidance goals. To derive a goal orientation factor, performance and performance avoidance goals were grouped together in contrast to learning goals. However, it is possible that college students adopt achievement strategies based not on the difference between learning and performance goals, but instead grounded in an approach verses avoidance framework (Elliot, 2005). Students who adopt learning goals and performance goals may seek out mastery-oriented strategies as part of an approach motivation, whereby each is motivated to achieve a positive expectant outcome. Students who employ performance avoidant goals, on the other hand, might more readily adopt helpless response patterns seeking to externalize the locus for potential failure (e.g., procrastinating in order to attribute outcomes to something other than ability).

Alternatively, the inability to identify a significant relationship between goal orientation and achievement strategies may be the result of the effects of social desirability. While the PALS scale for measuring students' goal orientation has demonstrated high convergent, construct, and discriminant validity (Jagacinski & Duda, 2001; Midgley et al., 1998), Tan and Hall (2005) have argued that a social desirability bias influences how students interpret and respond to the measure. Tan and Hall found that, among 239 college students, the failure to account for social desirability inflated how students respond to mastery-oriented and performance-avoidant goal items. Essentially, when students are asked whether or not they endorse mastery goal orientations, they are likely to do so not purely based on their implicit goal orientation but also because they believe a positive response will be viewed favorably by others. For students enrolled in a high-stakes STEM courses similar to those who participated in the present study, any occasion to demonstrate socially desirable qualities to faculty or researchers associated with their academic classes might seem important. Highly motivated students might seek any opportunity to impress their faculty or demonstrated their ability. Thus, the desire to answer in a socially acceptable manner might mask a truly significant relationship between goal orientation and achievement strategies. However, Tan and Hall (2005) recommend the PALS over other measures of goal orientation (e.g., VandeWalle's 1997 measure) due to its demonstrated smaller effects of social desirability. The present study was unable to tease out the moderating effects of social desirability in order to improve the overall model fit, and instead opted to modify the construct by removing two learning goal variables that were theoretically at odds with the remaining effect indicators to better represent the available data.

Finally, because this study is the first of its kind to assess the entirety of the hypothesized models' constructs according to a post-secondary population, it is possible that asking students to answer each item as part of one comprehensive survey may have biased the responses. Krosnick and Alwin (1987) were among the first cognitive psychologists to suggest that the order of survey questions may affect the comprehension and reporting processes that influence how survey participants respond. They suggest that to ease the cognitive load to better elicit valid and accurate responses, surveys might consider limiting the number of items or spreading them out among multiple examinations. However, asking students to respond to multiple surveys at different time periods can come with the high cost of participant attrition (Groves, Fowler, Couper, Lepkowski, Singer, & Tourangeau, 2009). Nevertheless, having answered the implicit theory, goal orientation, and achievement strategy items at one time may have introduced some form of response error in the data.

Academic Self-Perception

The principle concerns that led to hypothesizing an alternative model with an appended academic self-perception construct (ASP) were both theoretical and methodological. As previously noted, the hypothesized causal relationships shared between mindsets, goal orientation, and achievement strategies have been confirmed in a number of studies (e.g., Robins & Pals, 2002) and refuted in others (e.g., Dupeyrat & Marine, 2005). Considering the ambiguity resulting from these conflicting findings, the present study sought to account for this uncertainty by offering an alternative explanation of these relationships. To do so, a nested alternative hypothesis model was specified, estimated, and tested in stage two of this study. If specification of Dweck's (1999) original model resulted in significant parameter estimates for the causal relationships between mindsets, goal orientation, and achievement strategies, it was hypothesized that specification of an alternative model might offer a theoretical explanation for the incongruity found in past research. Simultaneously, the alternative model could be compared to Dweck's (1999) original model, offering an empirically sound method for determining the strength of Dweck's original specifications.

Measures of academic self-perception had originally been included in Dweck's initial theories concerning mindsets and motivation (see Dweck & Leggett, 1988). Dweck and Leggett (1988) hypothesized that entity theorists, when self-perceptions of academic merit were taken into account, would adopt divergent goal orientations: entity theorists with a high ASP would seek out performance goals, while entity theorists with low ASP would seek out performance-avoidant goals. Thus, accounting for ASP in the model could account for the shared variance between mindsets, goal orientation, and achievement strategies. Additionally, the evidence that suggests academic self-perceptions influence achievement outcomes is considerable (see Marsh & Craven, 2006; Pascarella & Terenzini, 2005; Schunk & Pajares, 2009).

As goal orientation failed to demonstrate a significant influence on achievement strategies in both Dweck's (1999) model and the alternative hypothesis models, the methodological purpose for appending ASP to the original model was rendered moot. Not only did the ill-fitting model provide unjustified parameter estimates, but comparison of the two ill-fitting models would not advanced the understanding of the relationships between the incorporated factors (Hancock, 2014).

It was also hypothesized that addition of the ASP construct would increase the absolute validity of Dweck's (1999) model. Improving absolute fit while simultaneously meeting thresholds of incremental and parsimonious fit provides a clearer explanation of the underlying causal effects between latent constructs in a model (Schumaker & Lomax, 2010). However, the alternative hypothesis model failed to meet acceptable absolute fit thresholds. Why did inclusion of the ASP construct not increase the explanatory power of the model? One possible explanation might be misspecification of the ASP construct in a post-secondary mindset model. Contrary to Dweck and Legget (1988) who found that academic self-perception moderates the relationships between mindsets and goal orientation, academic self-perception indictors failed to significantly correlate with mindset or goal orientation indicators. However, significant correlations were revealed between effort belief effect indicators and those of the academic self-perception construct, ranging from $\rho = .10$ to $\rho = .24$, $p < .05$. These correlation coefficients indicate that for students enrolled in introductory STEM courses, their academic self-perception is more related to their beliefs about effort rather than the goals they form or the strategies they choose to succeed.

It is possible that a feedback loop exists between beliefs about the utility of effort and academic self-perception, part of which could be specified in the model. Applied effort is widely considered to be a key factor in student learning and achievement, particularly in challenging or difficulty learning environments (Ambrose et al., 2010; Dweck, 2006). Scholars of teaching and learning also acknowledge that academic achievement influence students' academic self-perceptions (e.g., Marsh and Craven, 2006). Therefore, students who have high academic self-perceptions may have formed these perceptions in part because of their prior academic achievement that was based on applied effort. These high academic self-perceptions, in turn, reinforce the belief that effort is a useful tool worth employing. Utilizing Weiner's (1986) attribution theory as a theoretical framework, a conceptual model could therefore be developed to suggest that ASP influences effort beliefs. This specified relationship may improve the overall fit of

Dweck's (1999) original model and provide a better comparative model for evaluating individual causal relationships.

It is also possible that, similar to the measures for goal orientation, issues of order-effects, satisficing, and social desirability influenced the responses to the ASP indicators. While Marsh and O'Neill (1984) found no discernable order effects among the SDQ III items that measure self-concept, this was the first time that these items were measured in conjunction with the other motivational variables. This too is true of the Problem-Solving Self-Efficacy (Bandura, 2006) items. Because the self-concept and self-efficacy scales were ordered last among the seven construct scales, it is possible that students may have been biased by their responses to the previous measures when answering the self-concept and self-efficacy items. It is also possible that having answered 33 previous items, respondents felt the need to satisfice their answers due to survey fatigue. However, the varied response options for the self-concept (eight-point Likert response format as opposed to the previous six-point Likert response format) and self-efficacy (slider response format) should have limited the satisficing error (Krosnick, 1991). Finally, students may have responded to these items in a socially desirable manner that did not coincide the true beliefs of the respondents.

Limitations

Several limitations shape the nature and interpretation of both the results and conclusions provided by this study. Issues pertaining to the chosen methodology, data collection and subsequent data analyses, and the ability (or inability) to make accurate conclusions about the target population are discussed below.

One benefit of structural equation modeling (SEM) is the method's capacity to account for measurement error introduced by the data collection instrument. SEM accounts for such error by creating latent variables that are responsible for the shared variance-covariance between measured variables (Schumacker & Lomax, 2010). Given that the survey instruments were adopted from various sources and not necessarily tailored for the specific population, the ability to account for measurement error was desired. This benefit, however, comes at a cost. In order to accurately provide parameter estimates that account for measurement error, SEM requires both a large sample size and multivariate normality. Following the recommendations of Mueller and Hancock (2010) who suggest collecting at least 5 responses per parameter estimate, 2000 students were sampled resulting in a final sample of 501 respondents. This result provided a satisfactory ratio of 5.96 cases per parameter for the largest model tested. However, once the data was gathered, the assumption of univariate normality was violated. To account for the skewness and kurtosis found in the data, the ML χ^2, fit indices, and standard errors were adjusted according to the Satorra-Bentler (1988) scaling method as recommended by Finney and DiStefano (2013). While a ratio of 5.96 cases per parameter is an acceptable sample size for applying the Satorra-Bentler (1988) scaling method, it is smaller than the recommended size of 8 cases per parameter and may have introduced type II error (Mueller & Hancock, 2010).

The sample size was also insufficient to account for control variables. While data regarding students' race, ethnicity, gender, socioeconomic status, and prior academic achievement were collected, accounting for these factors would have exponentially increased the parameter estimates in the model and necessitated a considerably larger sample size. The feasibility of sampling the required number of students and receiving a sufficient number of responses was deemed improbable; therefore controls were not included in the analyses. Moreover, the primary purpose of this study was to test the utility of the model of implicit theories of intelligence with a college student population; thus, this study was exploratory and can serve as a baseline for future studies seeking to understanding how mindsets may vary by diverse populations. However, SEM provides error terms for each latent variable that account for the unexplained variance caused by unidentified factors not included in the model (Schumacker & Lomax, 2010).

Structural equation modeling also provides the unique ability to modify factor models when the validity of effect indicators cannot be adequately confirmed. As part of the present study, nine effect indicators failed to conform to their respective factors and were eliminated from analyses. While this modification improved the overall validity of each latent factor, the resulting constructs were not identical to those in other studies (e.g., Blackwell et al., 2007). Therefore, comparisons made between the achievement motivation of students at the K-12 level and post-secondary level are limited by these modifications to the constructs. However, it is important to note that changes made to the confirmatory factor models were conducted in light of theoretical considerations and not solely based on statistical evidence.

There are several issues related to the way the data was collected. The data itself was provided by self-report. It is possible that the observed scores collected from the self-administered survey instrument did not accurately represent the respondents' true beliefs or values (e.g., social desirability) (Tan & Rosalie, 2005). The students participating in this study may have answered the questions provided by the survey tool according to socially normative expectations. It is also possible that respondents lacked the reflective capacity or self-awareness to respond accurately to the hypothetical failure scenario provided in the Effort Orientation Inventory (Dweck & Sorich, 1999).

All subscales used to measure the motivational variables of the study employed either 6- or 8-point Likert-type scales. This use of even numbered scales on measures of valence limited the respondents ability to select a neutral position, in essence forcing an opinion. Consequentially, this technique may have collected erroneous data from those respondents that truly had no opinion or belief. However, Krosnick (1991) has suggested that survey respondents typically choose a “no opinion” option because they are looking to minimize the cognitive load normally required for surveys (a response behavior known as *satisficing*) and not because their belief is neutral. An even numbered scale requires additional effort from the participant in his/her interpretation, recall, and report of an answer. Therefore, it can be assumed that truthful responses from participants in the study were well considered.

A particular limitation of note was the use of end-of-course grades as the sole indicator for the academic achievement outcome criterion. A common understanding suggests that a host of factors (e.g., faculty subjectivity, differences in evaluation tools, effort) influence the reliability of using end-of-course grades as a referent for competence (Secolsky & Denison, 2012; Walvoord & Anderson, 1998). Though the inability to assess the reliability of the achievement outcome construct muddies the interpretation of the results, methodological decisions were made to limit the challenges to the validity of this construct. For example, introductory STEM courses were used to stratify the study sample since many course design elements of these classes emulate traditional high school coursework (Mastascusa et al., 2011). In particular, the majority of the STEM courses in the sampling frame employed multiple choice tests as the primary evaluation tool of student achievement in the classroom. When compared with other forms of evaluation (e.g., essays, student participation grades), multiple choice tests provide a more direct estimate of a student's mastery of course concepts (Gronlund, 1998). Therefore, due to the incorporation of these types of examinations into the student evaluation process, it is reasonable to hypothesize that the end-of-course grades collected in STEM courses represent a more reliable indicator of student competence (i.e., mastery of content) than other types of college courses and can therefore be operationalized as a sole indicator of student achievement.

The results are also subject to nonresponse bias. Of the sampled students who were asked to complete the self-administered survey, roughly half were women (μ = .507). Yet when the survey was concluded, nearly 62 percent of the cases had been provided by women in introductory STEM courses. This is not an uncommon phenomenon: Underwood, Kim, and Matier (2000) found that college women are more likely to respond to web-based surveys than college men. In light of the continual gender disparity in the entrance to and attainment of postsecondary STEM degrees (Hill, Corbett & St. Rose, 2010, Yoder, 2011), this data set has the potential to provide fascinating insight into the academic motivation of first- and second-year women enrolled in STEM coursework. Future research should consider the differences in achievement motivation for college men and women in these courses. However, it is important to note that for the present study, the data is not fully representative of a random sample given this nonresponse error.

It is also important to note that nearly 20 percent of respondents were not STEM majors. While this number does not significantly differ from the pool of students sampled for this study, this response pattern should be considered if accounting for measurement error. The sampling frame was composed of students enrolled in STEM courses for two reasons: (1) they have the potential to emulate the high-stakes academic environment of high school (Mastascusa et all., 2011) and provide enough challenge where the causal effects of mindsets on motivation can be measured (Grant & Dweck, 2003). However, it is possible the non-STEM majors may exhibit different motivational patterns than STEM majors enrolled in introductory STEM courses. While this measurement error is captured by SEM analysis, future research should take this limitation into account.

Finally, the college years remain a difficult time to accurately predict and measure aspects of students' psychosocial development. Many college students find themselves in environments that comprise the most heterogeneous populations they have ever come in contact with (Evans, Forney, Guido, Patton, & Renn, 2010). Simultaneously, few college students self-author their own beliefs; many continue to rely on external formulas for success (Baxter Magolda, 2001). Yet the varied environments within and across colleges and universities continue to influence how students develop from the first day on campus to their graduation. The psychosocial identities of college students can very widely between first-year and fourth-year students. While studies have suggested that without intervention, students' mindsets remain relatively stable in college (Grant & Dweck, 2003; Robins & Pals, 2002), colleges and universities are nevertheless places of intervention. From a psychosocial perspective, it is nearly impossible for students to escape the psychological impact of college environments (see Astin, 1991; Pascarella, 1985). To this end, it can be difficult to interpret structural models at the post-secondary level given the possibility that students' beliefs can change over their tenure in college. This is one reason why the analyses and conclusions in the present study were limited to first- and second-year students. This delimitation provides a somewhat homogenous population for assessment. However, conclusions from this study should not be applied to students who do not fit the demographics of the sampling frame.

Implications for Practice

As previously noted, the scholarship of teaching and learning at the post-secondary level is seemingly bereft of empirical evidence linking students' psychosocial approaches to the classroom to learning outcomes. This study provides such a link by offering a tenable explanation of how mindsets affect student motivation and achievement. At the same time, these findings offer faculty at the post-secondary level an avenue through which they can organize their pedagogy to improve learning outcomes in their classrooms. If instructors are exposed to the evidence that suggests that growth mindsets positively influence student motivation and achievement, they may be more inclined to adopt teaching strategies that nurture and leverage incremental theories of intelligence in their students. The key is to foster the belief that intelligence can change. This mindset then shapes an entire framework of student motivation, affecting what students value, how they respond to failure and success, and how they approach learning opportunities (Dweck, 1999).

But how can particular teaching strategies influence students to believe that intelligence is malleable? The answer may lie in the role mindsets play in determining the attributions students make for their successes and failures. The conceptual framework for this study suggests that mindsets serve as causal antecedents in Weiner's (1986) intrapersonal attribution theory of motivation (i.e., mindsets help students determine whether ability or effort is the root cause for their success or failure). Thus, growth mindsets act as cues that remind students about the utility of effort and in turn promote effective achievement strategies. If teaching strategies reinforce the idea that applied effort – rather than ability – will lead to success, students who embody a fixed mindset should begin to experience cognitive dissonance as a result of their attitudinal belief that ability, rather than effort, is the chief determinant for success. Research on the effects of cognitive dissonance suggests that individuals will seek methods for eliminating the psychological discomfort that is experienced as a result of the incongruent ideas (Elliot & Devine, 1994). Therefore, the dissonance felt by students with fixed mindsets should compel these entity theorists to reevaluate the mindset schema they use to make attributions. Continually emphasizing effort as the crucial factor for student success will consequentially modify students' causal antecedents by promoting growth, rather than fixed, mindsets. Similarly, designing activities and assessments that emphasize effort, such as review sessions, re-takeable quizzes, participation credit, or extra credit for optional homework will help scaffold a growth mindset orientation.

Two studies have already demonstrated how some instructional methods can influence students to adopt growth mindsets. Aronson and his colleagues (2002) found that they could significantly alter how students understand intelligence over the course of only 10 days by asking their students to write about the benefits of effort and hard work. By participating in three writing exercises, these students' self-beliefs in the malleability of intelligence began to strengthen. At the conclusion of the semester, many of these students earned higher end-of-course grades when compared to their counterparts who did not write about effort. Blackwell and her colleagues (2007) were able to engender growth mindsets through eight 25-minute workshops. These workshops provided readings, hands-on activities, and discussion that emphasized the malleability of intelligence. These interventions, like those previously mentioned, also resulted in higher grades for those who participated in the growth mindset workshops when compared to those in a control group.

At the heart of Dweck's (1999) theoretical claim that student mindsets affect motivation and achievement is the belief that faculty should assure students that they can succeed regardless of their intelligence. She writes:

> What's more, the confidence students need is *not* the confidence that they have a certain level of smartness, or that they have more of it than other students. The confidence they need is the confidence that they, or *anybody* for that matter, can learn if they apply their effort and strategies (pp. 57-58).

This tenant is integrally woven through Dweck's (1999; 2006) approach to teaching, yet it is not unique to her alone. In fact, validating the learner's capacity to know is a key principle of Baxter Magolda and King's (2004) Learning Partnerships Model (LPM). The LPM, developed by Baxter Magolda from her 17-year longitudinal study of adolescents moving through college and into emergent adulthood, is a pedagogical approach that promotes learning through challenge and simultaneous support. In addition to validating a student's capacity to create knowledge, the LPM asks faculty to adhere to two other key principles: learning should be situated in the learners' experiences, and learning should be defined as mutually constructing meaning. By adhering to these principles, Baxter Magolda and King believe instructors provide the support necessary for learners to construct knowledge as self-authors rather than receive knowledge as consumers. Baxter Magolda (2007) would later posit that it is only through *self-authorship*, or the ability to internally define one's beliefs and identity in relation to the outside world, that students can achieve advanced learning outcomes.

The LPM and its three key principles provide a framework for applying the findings from this study to instructional practice. To validate a student's capacity to know, instructors can seek to instill growth mindsets in their students. By providing opportunities for students to reflect on their educational experience, students may remember times when effort played an important role in their achievement. And when a classroom defines learning as mutually constructing meaning, the instructor imparts a sense of agency on behalf of the student that must be achieved through effort rather than demonstrated through ability. By designing classroom activities, homework, and assessments that incentivize effort, faculty can promote growth mindsets and consequentially increase student motivation.

In total, the revelation that growth mindsets increase achievement outcomes provides a deeper understanding of how students succeed in the classroom. The evidence suggests that learning is dependent on these psychological constructs. In the learning-centered paradigm – where academic success is reliant on student buy-in and engagement – it would benefit instructors to leverage this understanding of mindsets to encourage student motivation and achievement in their courses.

Suggestions for Future Research

The inability to validate Dweck's (1999) theoretical model as originally specified led the author to explore alternative models of achievement motivation. After a thorough analysis of the data fit, this study was able to specify and confirm a tenable model for achievement motivation that demonstrates empirical links between implicit theories of intelligence, motivation, and achievement outcomes. With any new model, additional studies should be conducted to validate the efficacy of the proposed model. Future research concerning this modified model of achievement motivation should include a full analysis of the structural model, including both confirmatory factor analyses and latent variable path analysis. These studies could also benefit from measuring goal orientation indicators in order to replicate Dweck's (1999) model for comparison. Measures of goal orientation might continue to borrow from the PALS scale (Midgley et al., 1998) or seek to redefine the construct according to Nichols (1989) task/ego involvement or Elliot (2005) approach/avoidance frameworks. And as previously noted, due to the chance of nonnormality in the sample data, future studies should seek to increase the sample sizes of students and response rates.

The sample data set in this study was composed of responses from multiple groups of students. Multi-group comparisons should be able to provide additional insight into how (or if) particular sub-groups leverage mindsets to influence motivation and achievement. For example, we know that women are less likely to attain post-secondary STEM degrees that men (Hill, Corbett & St. Rose, 2010, Yoder, 2011). Some scholars have suggested that this discrepancy is partially due to the presence of stereotype threat (Keller & Dauenheimer, 2003; Shapiro & Williams, 2012). Could women who are enrolled in STEM courses or are majoring in STEM fields operationalize mindsets in a different manner than men to combat this stereotype threat? Aronson and his colleagues (2002) found that growth mindsets can combat stereotype threat and reduce achievement gaps. It is therefore plausible that the proposed model operates differently for different subgroups. Future research should investigate these differences, including but not limited to groups based on race, gender, socioeconomic status, undergraduate major, and prior academic achievement. Future studies could also expand the sampling frame to include different academic disciplines (e.g., the humanities or pre-professional studies) or additional institutional types (liberal arts, community colleges); this analysis could provide greater between-department/institution effects that would be important for further extrapolation of the findings.

In an *a priori* attempt to account for some discrepancies found in the goal orientation literature, this study analyzed a hypothetical model that appended measures of academic self-perception to Dweck's (1999) original model. Yet because Dweck's model failed to demonstrate significant links between goal orientation and achievement strategies (reflecting the literature discrepancies), the addition of this measure did not enhance the understanding of achievement motivation according to the model's specifications. Future analyses of the tenable modified model could benefit by measuring students academic self-perceptions. This factor could then be used to control for divergent self-perceptions, or the factor could be appended to the modified model to investigate whether or not academic self-perceptions play a distinct role in achievement motivation as hypothesized by this study. It is also theoretically possible that the relationships between academic self-perception, goal orientation, achievement strategies, and achievement outcomes were misspecified. Further investigations may consider new or additional specifications to more appropriately capture the influence of this construct on mindsets and achievement motivation.

Finally, future researchers might consider the effects of the modified model of mindsets and achievement motivation on contemporary teaching and learning models. For example, John Keller (2010) has developed the ARCS Model of Motivation Design, which suggests that instructors should focus on promoting attention, relevance, confidence, and satisfaction to promote and sustain student motivation in the classroom. Understanding the interplay between the mindset framework of motivation and models such as the ARCS can further scholarship by revealing the conditional effects of motivation frameworks and strengthen instruction by providing faculty with methods to structure their pedagogy in order to account for these interactions.

Conclusion

College and university instructors are slowly yet assuredly inviting students to take part in the co-construction of knowledge as part of a learner-centered approach to education. This shift requires students to assume a greater deal of agency in their achievement outcomes. To this end, it is important that scholars of teaching and learning identify those aspects of student motivation that affect learning outcomes and can be leveraged by instructors to improve student buy-in and success. This study provided empirical evidence to suggest that particular psychological constructs – student mindsets – most likely play a causal role in the achievement outcomes of first- and second-year students enrolled in STEM courses at the post-secondary level. In particular, results from the study indicate that growth mindsets have the potential to influence positive aspects of motivation that contribute to increases in academic achievement (namely end-of-course grades).

The model revealed by this study suggests that while a causal relationship likely exists between mindsets and student achievement, the influence of growth mindsets on high achievement might not be mediated by the incremental theorists' adoption of learning or performance mastery goals: a relationship that had originally been hypothesized by Dweck (1999; 2006). Instead, growth mindsets influence the belief that effort is a necessary part of learning. This belief then shapes the strategies students adopt in learning opportunities and forms in students a resilient attitude towards failure. In turn, students with a growth mindset are rewarded with better grades in challenging coursework.

This model of achievement motivation provides a framework for understanding how students approach learning opportunities. By designing pedagogical approaches that encourage growth mindset formation, faculty can increase the motivation of their students and simultaneously improve the chances that students will succeed in the classroom. In particular, faculty who instill a belief in their students that intelligence can be cultivated provide a meaningful way of validating their students' capacity to learn: a significant step in promoting advanced learning outcomes (Baxter Magolda, 2007).

This study reemphasizes the capacity for all students to learn and succeed at the post-secondary level. Students do not need confidence in their abilities; rather, they should be reminded that diligent effort has the potential to cultivate learning and success. As Dweck (2006) so eloquently reminds us, "Although people may differ in every which way – in their initial talents and aptitudes, interests, or temperaments – everyone can change and grow through application and experience" (p. 7). Growth mindsets instill this sense of promise and pave the way for real accomplishment and student success.

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APPENDIX A

DESCRIPTION OF COURSES IN SAMPLING FRAME

Subject	Course Title	Course Description
Applied Mathematics	Single Variable Calculus II	Includes the concepts of differential and integral calculus and applications to problems in geometry and elementary physics, including inverse functions, indeterminate forms, techniques of integration, parametric equations, polar coordinates, infinite series, including Taylor and Maclaurin series. Applications.
Applied Mathematics	Multivariable Calculus	Topics include vectors in three-space and vector valued functions. The multivariate calculus, including partial differentiation, multiple integrals, line and surface integrals, and the vector calculus, including Green's theorem, the divergence theorem, and Stokes's theorem. Applications.
Applied Mathematics	Ordinary Differential Equations	First order differential equations, second order and higher order linear differential equations, reduction of order, undetermined coefficients, variation of parameters, series solutions, Laplace transforms, linear systems of first order differential equations and the associated matrix theory, numerical methods. Applications.
Biology	Introduction to Biology: Organismal and Evolutionary Biology	Intensive introduction to modern biology designed for natural science majors. Biological structure and function at various levels of organization, cell biology, genetics, development and evolution are covered. This course is required for all biology majors and is a prerequisite for most upper-level biology courses. Lectures and recitation/review.
Biomedical Engineering	Biomedical Engineering Design and Discovery	Provides overview of the BME discipline and major sub-disciplines (biomechanics, genetic engineering, tissue engineering, bioelectricity, imaging, cellular engineering, computational systems biology), covers conceptual and detail design processes, and introduces quantitative tools utilized throughout the BIOM curriculum.
Biomedical Engineering	Physiology II	Introduces the physiology of the kidney, salt and water balance, gastrointestinal system, endocrine system, and central nervous system, with reference to diseases and their pathophysiology.
Biomedical Engineering	Cell and Molecular Biology for Engineers	Introduces the fundamentals of cell structure and function, emphasizing the techniques and technologies available for the study of cell biology. Divided into three general sections: cell structure and function includes cell chemistry, organelles, enzymes, membranes, membrane transport, intracellular compartments and adhesion structures; energy flow in cells concentrates on the pathways of glycolysis and aerobic respiration; information flow in cells focuses on modern molecular biology and genetic engineering, and includes DNA replication, the cell cycle, gene expression, gene regulation, and protein synthesis. Also presents specific cell functions, including movement, the cytoskeleton and signal transduction.
Chemistry	Introductory College Chemistry / Introductory College Chemistry for Engineers	Introduces the principles and applications of chemistry. Topics include stoichiometry, chemical equations and reactions, chemical bonding, states of matter, thermochemistry, chemical kinetics, equilibrium, acids and bases, electrochemistry, nuclear chemistry, and descriptive chemistry of the elements. For students planning to elect further courses in chemistry, physics, and biology.
Chemistry	Principles of Organic Chemistry (Accelerated)	Seeks to understand elementary reaction types as a function of chemical structure by emphasizing organic compounds. Topics include acid-base, nucleophilic substitution, oxidation-reduction, electrophilic addition, elimination, conformational analysis, stereochemistry, aromaticity, and molecular spectroscopy.
Computer Science	Introduction to Information Technology	Introduces the basic principles and concepts of object-oriented programming through a study of algorithms, data structures and software development methods in Java. Emphasizes both synthesis and analysis of computer programs.
Computer Science	Introduction to Programming	Introduces the basic principles and concepts of object-oriented programming through a study of algorithms, data structures and software development methods in Java. Emphasizes both synthesis and analysis of computer programs. Prerequisite: Prior programming experience.
Computer Science	Introduction to Programming	Introduces the basic principles and concepts of object-oriented programming through a study of algorithms, data structures and software development methods in Java. Emphasizes both synthesis and analysis of computer programs. Note: No prior programming experience allowed.

Environmental Science	Introduction to Environmental Science	Introduces the principles and basic facts of the natural environment. Topics include earth materials, land forms, weather and climate, vegetation and soils, and the processes of environmental change and their implications to economic and human systems
Mathematics	Calculus I	Introduces calculus with emphasis on techniques and applications. Recommended for natural science majors and students planning additional work in mathematics. The differential and integral calculus for functions of a single variable is developed through the fundamental theorem of calculus.
Mathematics	Calculus II	Applications of the integral, techniques of integration, infinite series, vectors.
Physics	General Physics	First semester of introductory physics for engineers. Classical mechanics, including vector algebra, particle kinematics and dynamics, energy and momentum, conservation laws, rotational dynamics, oscillatory motion, gravitation, thermodynamics, and kinetic theory of gases.
Physics	Introductory Physics II: Gravitation, Oscillations, Waves & Thermodynamics	Second semester of a four-semester sequence for prospective physics and other science majors. Topics include gravitation and Kepler's laws; harmonic motion; thermodynamics; wave motion; sound; optics.
Physics	Principles of Physics II	Constitutes terminal course sequence covering the principles of mechanics, heat, electricity and magnetism, optics, atomic, solid state, nuclear, and particle physics.
Physics	General Physics II	Second semester of introductory physics for engineers. Electrostatics, including conductors and insulators; DC circuits; magnetic forces and fields; magnetic effects of moving charges and currents; electromagnetic induction; Maxwell's equations; electromagnetic oscillations and waves. Introduces geometrical and physical optics.
Statistics	Introduction to Statistical Analysis	Introduction to the probability and statistical theory underlying the estimation of parameters and testing of statistical hypotheses, including those arising in the context of simple and multiple regression models. Students will use computers and statistical programs to analyze data. Examples and applications are drawn from economics, business, and other fields.

APPENDIX B

RESEARCH INSTRUMENT SCALES & SUPLEMENTAL ITEMS

Theories of Intelligence Scale for Adults (Dweck et al., 1995)

The following questions seek to understand ideas about intelligence. There are no right or wrong answers. We are interested in your ideas.

Using the scale provided, please indicate the extent to which you agree or disagree with each of the following statements.

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

1. You have a certain amount of intelligence, and you can't really do much to change it. (ent1)

2. Your intelligence is something about you that you can't change very much. (ent2)

3. You can learn new things, but you can't really change your basic intelligence. (ent3)

Task Goal Orientation Scale (Midgley et al., 1998)

The following questions have been designed to investigate approaches to coursework. There are no right or wrong answers.

Using the scale provided, please indicate the extent to which you agree or disagree with each of the following statements.

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

1. I like course work best when I can do it perfectly without any mistakes. (perf1)
2. An important reason why I study is because I like to learn new things. (learn1)
3. The main thing I want when I do my course work is to show how good I am at it. (perf2)
4. It's very important to me that I don't look stupid in class (avoid1)
5. I like course work best when it makes me think hard. (learn2)
6. I like course work best when I can do it really well without too much trouble. (perf3)
7. An important reason why I do my schoolwork is so I won't embarrass myself. (avoid2)
8. I like course work that I'll learn from even if I make a lot of mistakes (learn3)
9. Sometimes I would rather perform well in class than learn a lot. (perf4)
10. An important reason I do my work for class is so others won't think I'm dumb. (avoid3)
11. It's much more important for me to learn things in my classes than it is to get the best grades. (learn4)

Effort Orientation Inventory – Effort Beliefs Subscale (Dweck & Sorich, 1999)

The following questions seek to understand ideas about effort. There are no right or wrong answers. We are interested in your ideas.

Using the scale provided, please indicate the extent to which you agree or disagree with each of the following statements.

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

1. To tell the truth, when I work hard at my schoolwork, it makes me feel like I'm not very smart. (negeff1)

2. It doesn't matter how hard you work – if you're not smart, you won't do well. (negeff2)

3. When something is hard, it just makes me want to work more on it, not less. (poseff1)

4. If you're not good at a subject, working hard won't make you good at it. (negeff3)

5. If an academic discipline is hard for me, it means I probably won't be able to do really well at it. (negeff4)

6. If you're not doing well at something, it's better to try something easier. (negeff5)

7. If you don't work hard and put in a lot of effort, you probably won't do well. (poseff2)

8. The harder you work at something, the better you will be at it. (poseff3)

9. If an assignment is hard, it means I'll probably learn a lot doing it. (poseff4)

Effort Orientation Inventory – Failure Attribution and Academic Effort Strategies Subscales (Dweck & Sorich, 1999)

The following questions ask you to respond to a scenario. When you read the scenario, pretend that it really happened to you and try to picture how you would feel and what you would do if it happened.

Scenario:

Imagine that during your second semester at (MaU), you take an important course in your major. You think you know the subject pretty well, so you study a medium amount for the first quiz. When you take the quiz, you think you did okay, even though there were some questions you didn't know the answer for. Then the class gets their quizzes back and you find out your score: you only got a 54, and that's an F.

What would you think was the main reason why you failed the quiz? Using the scale provided, please indicate how true you think each of these reasons is.

1	2	3	4	5	6
Very True	True	Slightly True	Slightly False	False	Totally False

The reason was…

1. I wasn't smart enough. (helples1)
2. I didn't study hard enough. (effort1)
3. The quiz was unfair or too hard for the class. (helples2)
4. I'm just not good at this subject. (helples3)
5. I didn't go about studying in the right way. (effort2)
6. I didn't really like the subject that much. (helples4)

What do you think you would do next? Using the scale provided, please indicated how much you think you would do each of these things.

1. I would spend less time on this class from now on. (negstat1)
2. I would try not to take this subject ever again. (negstat2)
3. I would spend more time studying for tests. (posstat1)
4. I would work harder in this class from now on. (posstat2)

Domain-Specific Perceived Self-Concept Scale (Marsh & O'Neill, 1984).

You were invited to participate in this study because you are currently enrolled in a (subject domain) *course at MaU. As such, we hope to understand how you think about* (subject domain).

Using the scale provided, please indicate the extent to which you believe the following statements range from definitely true or definitely false.

1	2	3	4	5	6	7	8
Definitely True	True	Mostly True	More True Than False	More False Than True	Mostly False	False	Definitely False

1. I find many (scientific, technological, engineering, mathematical) problems interesting and challenging. (spc1)
2. I have hesitated to take courses that involve (science, technology, engineering, mathematics). (spc2)
3. I have generally done better in (science, technology, engineering, mathematics) courses than other courses. (spc3)
4. (Science, technology, engineering, mathematics) makes me feel inadequate. (spc4)
5. I am quite good at (science, technology, engineering, mathematics). (spc5)
6. I have trouble understanding anything that is based upon (science, technology, engineering, mathematics). (spc6)
7. I have always done well in (science, technology, engineering, mathematics) classes. (spc7)
8. I never do well on tests that require (scientific, technological, engineering, mathematical) reasoning. (spc8)
9. At school, my friends always came to me for help in (science, technology, engineering, mathematics). (spc9)
10. I have never been very excited about mathematics. (spc10)

Problem-Solving Self-Efficacy Scale (Bandura, 2006)

Please rate how certain you are that you will be able to solve the academic problems in you [course title] class on the next exam according to each of the levels described below.

Rate your degree of confidence by recording a number from 0 to 100 using he scale given below:

0	10	20	30	40	50	60	70	80	90	100
Cannot do at all					Moderately can do					Highly certain can do

					Confidence (0-100)
Can solve	10%	of	the	problems	____
“	20%	“	“	“	____
“	30%	“	“	“	____
“	40%	“	“	“	____
“	50%	“	“	“	____
“	60%	“	“	“	____
“	70%	“	“	“	____
“	80%	“	“	“	____
“	90%	“	“	“	____
“	100%	“	“	“	____

Additional Data to be Collected from MaU's Office of Institutional Assessment

1. Student's year in school
2. Student's age
3. Student's zip code
4. Student's high school GPA
5. Student's SAT score
6. Number of advanced placement (AP) classes student took while in high school
7. Race
8. Gender
9. Mother's level of education
10. Pell grant recipient

APPENDIX C

PRE-NOTICE LETTER OF SELECTION FOR PARTICIPATION IN RESEARCH STUDY

Dear [MaU] Student,

You have been selected to participate in a survey as part of a research study into the effects of motivation on academic achievement among first- and second-year college students at MaU. Your participation will provide valuable information that will be used to inform how students at MaU approach learning opportunities in the classroom. Participation is voluntary, and your participation in the survey will remain confidential and will in no way affect your grades or standing at the University.

If you elect to participate in the survey, you will be entered into a drawing to receive one of ten $50 gift card to Amazon.com. Winners will be notified of their selection three weeks after the survey is closed.

Next Monday, January 27th, please look for an email that will contain a link to participate in the survey. If you have questions, please feel free to contact the principle investigator of the research project listed below.

Sincerely,
Bo Odom

Clarence “Bo” Guy Odom, IV
Principle Investigator
Olsson Hall 228
University of Virginia
Charlottesville, Virginia 22904
Phone: 865-603-9343
Email: cgo3tc@virginia.edu

Distribution of this letter has been approved by the Office of the Vice President and Chief Student Affairs Official, MaU.

APPENDIX D

PARTICIPANT CONSENT FORM

The primary purpose of this study is to understand how motivation plays a role in academic achievement among first- and second-year college students. Results and recommendations discovered in this study will be provided to [MaU] in order to benefit the understanding of teaching and learning [at MaU]. The data collected in this study will be published in a doctoral dissertation and any publications stemming from the dissertation. Your participation in this study will involve completing a survey during the beginning of the Spring, 2014 semester. The estimated time necessary to complete the survey is 30 minutes. There are no anticipated risks related to participation in this study. Participation in this study is completely voluntary. You may discontinue participation in the study at any time. If you wish to withdraw, please discontinue the survey. You may also elect not to answer any questions that you feel uncomfortable answering. If you would like to withdraw after completing the survey, please contact the Principle Investigator listed below.

The benefits that you may expect to gain from participating include the following: (1) knowledge that you are benefiting the scholarship of teaching and learning in higher education; and (2) participation into the survey enters you into a drawing for one of ten $50 gift cards to Amazon.com. Chances of winning one of these gift cards depend on the number of respondents to the survey.

The data you provide by responding to the survey will be handled confidentially. After collection of the data, the information will be supplied to [MaU's] Office of Institutional Assessment (OIA). The OIA will add pertinent demographic information to the data then make the data anonymous by removing any personal identifying information before resending to the Principle Investigator. This information will remain anonymous throughout the duration of analysis. Your name or identifying information will not be used in any report.

If issues of concern arise while you are taking the survey, please contact:

Clarence "Bo" Guy Odom, IV
Principle Researcher
Olsson Hall 228
University of Virginia
Charlottesville, VA 22904
Phone: 865-603-9343
cgo3tc@virginia.edu

Karen K. Inkelas
Dissertation Chair
Olsson Hall 214
University of Virginia
Charlottesville, VA 22904
434-243-1943
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Questions regarding your rights in this study can be directed to [Mau's] Institutional Review Board for the Social and Behavioral Sciences. Contact [redacted], phone number [redacted] or email [redacted].

______________________________ ______________

Signature Date

APPENDIX E

CODE BOOK FOR MEASURED VARIABLES

Item	Description	Variable Mnemonic	Label	Value
1	Response ID	ID	ID	
2	The subject domain under which the student's academic course is classified.	Domain	Subject Domain	1- Science 2- Technology 3- Engineering 4- Math
3	Student's year in school.	Year	Year in School	1- First-Year 2- Second- Year
4	Student's age.	Age	Age	
5	Student's zip code.	Zip	Zip Code	
6	Student's high school Grade Point Average (GPA)	GPA	GPA	
7	Score on SAT Verbal	SATV	SAT Verbal	
8	Score on SAT Math	SATM	SAT Math	
9	Score on SAT Writing	SATW	SAT Writing	
10	Composite SAT score as an average of SAT Verbal, SAT Math, and SAT Writing	SAT	SAT Composite	
11	Composite score on ACT	ACT	ACT Composite	
12	College credits already accumulated prior to matriculation	Credits	Credits Earned	
13	Reported race for IPEDS reporting	Race	Race	0- White 1- African-American 2- Hispanic 3- American Indian 4- Asian 5- Multi-Race 6- Non-Resident Alien 7- Race and Ethnicity Unknown
14	Student self-report as African American	RaceAA	African-American	0 – No 1 – Yes
15	Student self-report as American Indian	RaceAI	American-Indian	0 – No 1 – Yes
16	Student self-report as Asian	RaceA	Asian	0 – No 1 – Yes
17	Student self-report as Hispanic	RaceHis	Hispanic	0 – No 1 – Yes
18	Student self-report as Native Hawaiian	RaceHAW	Hawaiian	0 – No 1 – Yes
19	Student self-report as White	RaceW	White	0 – No 1 – Yes
20	Gender	Gender	Gender	0 – Male 1 – Female
21	Mother's Reported Level of Education	MEduc	Mother's Education	0 – College 1 – High School 2 – Elementary 99 – Unknown / Did not report
22	Did the student receive financial aid in the form of a Pell grant	Pell	Pell Grant	0 – no 1 – yes

23	Did the student demonstrate need for financial aid above and beyond Pell need	NonPell	Non-Pell need	0 – no 1 – yes
24	You have a certain amount of intelligence, and you can't really do much to change it.	ENT1	Entity Mindset 1	1 – Strongly Agree 2 – Agree 3 – Slightly Agree 4 – Slightly Disagree 5 – Disagree 6 – Strongly Disagree
25	Your intelligence is something about you that you can't change very much	ENT2	Entity Mindset 2	…
26	You can learn new things, but you can't really change your basic intelligence	ENT3	Entity Mindset 3	…
27	I like course work best when I can do it perfectly without any mistakes	PERF1	Performance Goal 1	…
28	The main thing I want when I do my course work is to show how good I am at it.	PERF2	Performance Goal 2	…
29	I like course work best when I can do it really well without too much trouble.	PERF3	Performance Goal 3	…
30	Sometimes I would rather perform well in class than learn a lot	PERF4	Performance Goal 4	…
31[a]	An important reason why I study is because I like to learn new things.	LEARN1	Learning Goal 1	…
32[a]	I like course work best when it makes me think hard.	LEARN2	Learning Goal 2	…
33[a]	I like course work that I'll learn from even if I make a lot of mistakes	LEARN3	Learning Goal 3	…
34[a]	It's much more important for me to learn things in my classes than it is to get the best grades.	LEARN4	Learning Goal 4	…
35	It's very important to me that I don't look stupid in class	AVOID1	Avoidance Goal 1	…
36	An important reason why I do my schoolwork is so I won't embarrass myself.	AVOID2	Avoidance Goal 2	…
37	An important reason I do my work for class is so others won't think I'm dumb.	AVOID3	Avoidance Goal 3	…
38	To tell the truth, when I work hard at my schoolwork, it makes me feel like I'm not very smart.	NEGEFF1	Negative Effort 1	…
39	It doesn't matter how hard you work – if you're not smart, you won't do well	NEGEFF2	Negative Effort 2	…
40	If you're not good at a subject, working hard won't make you good at it.	NEGEFF3	Negative Effort 3	…
41	If an academic discipline is hard for me, it means I probably won't be able to do really well at it.	NEGEFF4	Negative Effort 4	…
42	If you're not doing well at something, it's better to try something easier.	NEGEFF5	Negative Effort 5	…
43[a]	When something is hard, it just makes me want to work more on it, not less	POSEFF1	Positive Effort 1	…
44[a]	If you don't work hard and put in a lot of effort, you probably won't do well.	POSEFF2	Positive Effort 2	…

45[a]	The harder you work at something the better you will be at it.	POSEFF3	Positive Effort 3	…
46[a]	If an assignment is hard, it means I'll probably learn a lot doing it	POSEFF4	Positive Effort 4	…
47	[Reason for failing] I wasn't smart enough	HELPLES1	Helpless 1	1 – Very True 2 – True 3 – Slightly True 4 – Slightly False 5 – False 6 – Totally False
48	[Reason for failing] The quiz was unfair or too hard for the class	HELPLES2	Helpless 2	…
49	[Reason for failing] I'm just not good at this subject	HELPLES3	Helpless 3	…
50	[Reason for failing] I didn't really like the subject that much.	HELPLES4	Helpless 4	…
51[a]	[Reason for failing] I didn't study hard enough	EFFORT1	Effort 1	…
52[a]	[Reason for failing] I didn't go about studying in the right way	EFFORT2	Effort 2	…
53[a]	[Academic Strategies] I would spend more time studying for tests.	POSSTAT1	Positive Strategies 1	…
54[a]	I would work harder in this class from now on.	POSSTAT2	Positive Strategies 2	…
55	[Academic Strategies] I would spend less time on this class from now on.	NEGSTAT1	Negative Strategies 1	…
56	[Academic Strategies] I would try not to take this subject ever again	NEGSTAT2	Negative Strategies 2	…
57[a]	I find many (domain category) problems interesting and challenging.	SC1	Self-Concept 1	1 – Definitely True 2 – True 3 – Mostly True 4 – More True than False 5 – More False than True 6 – Mostly False 7 – False 8 – Definitely False
58	I have hesitated to take courses that involve (domain category).	SC2	Self-Concept 2	…
59[a]	I have generally done better in (domain category) courses than other courses.	SC3	Self-Concept 3	…
60	(Domain category) makes me feel inadequate	SC4	Self-Concept 4	…
61[a]	I am quite good at (domain category)	SC5	Self-concept 5	…
62	I have trouble understanding anything that is base upon (domain category).	SC6	Self-Concept 6	…
63[a]	I have always done well in (domain category) classes	SC 7	Self-Concept 7	…
64	I never do well on tests that require (domain category) reasoning	SC8	Self-Concept 8	…
65[a]	At school, my friends always came to me for help in (domain category)	SC9	Self-Concept 9	…
66	I have never been very excited about (domain category).	SC10	Self-Concept 10	…

67	Can solve 10% of the problems	SE1	Self-Efficacy 1	0 – 100
68	Can solve 20% of the problems	SE2	Self-Efficacy 2	…
69	Can solve 30% of the problems	SE3	Self-Efficacy 3	…
70	Can solve 40% of the problems	SE4	Self-Efficacy 4	…
71	Can solve 50% of the problems	SE5	Self-Efficacy 5	…
72	Can solve 60% of the problems	SE6	Self-Efficacy 6	…
73	Can solve 70% of the problems	SE7	Self-Efficacy 7	…
74	Can solve 80% of the problems	SE8	Self-Efficacy 8	…
75	Can solve 90% of the problems	SE9	Self-Efficacy 9	…
76	Can solve 100% of the problems	SE10	Self-Efficacy 10	…
77	Summed score for Self-Concept Scale	SC	Self-Concept	0 – 80
78	Summed score for Low Difficulty Self-Efficacy Items ,1 – 5	SE15	Self-Efficacy 1-5	0-500
79	Summed score for High Difficulty Self-=Efficacy Items, 6 – 10	SE610	Self Efficacy 6 – 10	0-500
80	End-of-course grade	EOCG	Final Grade	0.00 – 4.00

Note. [a]Reverse coded for analysis.