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Predicting Undergraduate Statistics Course Performance and Transfer through Students' Implicit Theories and Achievement Goals

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PREDICTING UNDERGRADUATE STATISTICS COURSE PERFORMANCE AND TRANSFER THROUGH STUDENTS' IMPLICIT THEORIES AND ACHIEVEMENT GOALS

by

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Abstract

Students' implicit theories of intelligence (TOI), implicit theories of statistics ability (TOSA), and achievement goals were analyzed as individual differences predictors of both statistics course performance and statistics transfer. Students enrolled in an introductory undergraduate statistics course completed inventories for the three individual differences under investigation as well as measures of course performance and transfer. We hypothesized that TOSA would be would be a stronger predictor of achievement goals, course performance, and transfer, and would outperform TOI in competing path models. We also anticipated that achievement goals would predict both statistics outcomes. Results demonstrated that (1) TOSA is a stronger predictor of achievement goals than TOI, (2) course performance is predicted negatively by entity TOSA and positively by mastery approach achievement goals, and (3) transfer is negatively predicted by performance avoidance achievement goals and entity theory of statistics ability. Results of path analysis were inconclusive.

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Predicting Undergraduate Statistics Course Performance and Transfer through Students' Implicit Theories and Achievement Goals

An understanding of statistics is required for success in a number of professional fields as well as in many undergraduate and graduate programs including psychology. Not only is statistics knowledge important in academic and professional settings, however, it is also beneficial for interpreting medical, political, and advertising claims as well as other information encountered in daily life. Unfortunately, while statistics education is both widely implemented and highly useful, the path to statistics success is often a difficult one. In order for educators and curriculum developers to overcome the barriers to statistics knowledge, it is the charge for researchers to understand how students' individual differences uniquely and in combination promote or prohibit success.

Statistics anxiety is perhaps the most investigated deterrent to statistics success, estimated to be experienced by up to 80% of students when they encounter any form of statistics information (Onwuegbuzie & Wilson, 2003). While statistics anxiety is widely studied and quite prevalent among students (Cruise, Cash, & Bolton, 1985; Hanna, Shevlin, & Dempster, 2008; Lalonde & Gardner, 1993; Onwuegbuzie, 2003, 2004), it is far from the only variable contributing to statistics success. Many lines of research demonstrate that statistics anxiety relates to other variables when predicting statistics performance such as trait anxiety (Macher, Paechter, Papousek, & Ruggeri, 2012), culture and gender (Baloglu, Deniz, & Kesici, 2011), and procrastination (Onwuegbuzie, 2004). While the role of statistics anxiety has been thoroughly investigated, however, less research has focused on the potential influences of students' implicit theories and goal orientations for statistics performance.

The motivation behind investigating implicit theories and goal orientations separate from statistics anxiety stems first from evidence that both implicit theories and goals have the potential to predict classroom and academic outcomes (Blackwell, Trzesniewski, & Dweck, 2007; Church, Elliot, & Gable, 2001; Elliot & Church, 1997; Elliot & McGregor, 1999, 2001; Elliot & Murayama, 2008; Grant & Dweck, 2003; Harackiewicz, Barron, & Elliot, 1998; Harackiewicz, Barron, Tauer, Carter, & Elliot, 2000; Henderson & Dweck, 1990; Pekrun, Elliot, & Maier, 2009). Another important motivation is that while interventions that directly target statistics anxiety may be difficult to implement, implicit theories interventions have been used in education contexts with reported success (Aronson, Fried, & Good 2002; Blackwell et al., 2007; Cohen, Garcia, Purdie-Vaughans, Apfel & Brzustoski, 2009) and, if successful, may result in a decrease in statistics anxiety alongside an increase in statistics success. Interventions which target achievement goals have also begun to be successfully implemented (Bernacki, Nokes-Malach, Richey & Belenky, 2016), and the theoretical relationship between implicit theories and goals motivates a decision to investigate both paradigms in the context of one another to understand whether or not implicit theories interventions might influence goal orientations and to understand whether or not goal orientation interventions ought to be considered. If implicit theories or goals do predict success, future work should test whether or not implicit theories or goals specific interventions remediate statistics anxiety in addition to improving outcomes.

Achievement Goals

When students engage in academic tasks, they necessarily have some goal that guides their efforts, some reason why they choose to engage. These goals can include things like “I want to gain more knowledge in this area,” “I want to pass this course with a respectable grade,” and “I want to avoid failing this course.” Goal orientation theory, rather than encompassing any and all possible reasons for academic engagement, posits that students will fall along two types of orientations, performance or mastery, which are then predictive of classroom outcomes (Church et al., 2001; Elliot & Church, 1997; Elliot & McGregor, 1999, 2001; Elliot & Murayama, 2008; Grant & Dweck, 2003; Harackiewicz et al., 1998; Harackiewicz et al., 2000; Pekrun et al., 2009). Students with performance orientation are motivated by the desire to compare favorably against others. Students with mastery orientation, on the other hand, are motivated by the desire for self-improvement. While earlier work on goal orientation (e.g., Ames, 1984; Dweck, 1986; Nicholls, 1984) focuses solely on mastery vs. performance in a two-factor framework, Elliot and colleagues have suggested a three-factor (tripartite) framework (Elliot & Church, 1997) and a two-by-two framework (Elliot & McGregor, 2001). Elliot and McGregor (2001) define the two-by-two framework on the axes of goal definition (mastery or performance) and goal valence (approach or avoidance). For goal definition, mastery and performance are defined in the same way as they were originally defined in the two-factor framework. For goal valence, a student can be motivated either by actively approaching success (approach valence) or actively avoiding failure (avoidance valence.) In the two-by-two definition, then, students will hold one of four goals based on where they fall on each axis. Students who hold mastery approach goals are actively attempting to improve their ability while students who hold performance approach goals are actively attempting to perform well compared to peers. Students who hold mastery avoidance goals, conversely, are attempting to avoid personal failure while students with performance avoidance goals are attempting to avoid comparative failure (i.e. being seen as doing less well compared to others.)

Through expanding the model to a two-by-two, achievement goals are more easily tied to classroom behaviors. Dweck (1986) argues that students with performance goals will seek out challenges if their confidence in their current ability is high, but will avoid challenges if their confidence in their current ability is low. We could consider the high-confidence performers to be performance-approach and the low-confidence to be performance-avoidance. While Dweck believes that all students with mastery goals will seek out challenges, it seems that the fourth variable added to goal orientation theory, mastery avoidance, is a challenge to that belief. While mastery avoidance has been little studied, it posits that students' may have a desire to avoid performing poorly outside of a performance orientation. We believe that in the context of statistics performance, these students will behave similarly to those with performance avoidance, i.e. that their desire to avoid failure will likewise lead them to avoid classroom challenges.

With many studies demonstrating that achievement goals can predict academic outcomes, different studies have found different significant predictors among goal orientations. Elliot and McGregor (2001) made two important findings regarding goals and study strategies. They found that mastery approach goals are a positive predictor of deep processing, a study strategy characterized by intentional engagement with course materials. They found that performance avoidance goals, however, are a positive predictor of shallow processing, which is conceptually opposed to deep processing and characterized by rote memorization of materials. They also found that, when predicting exam scores, performance approach goals were a positive predictor of overall performance, multiple choice performance, and short answer performance, whereas performance avoidance goals were a negative predictor for all three. Elliot and Murayama (2008) also found that performance approach positively predicts classroom performance, while performance avoidance is a negative predictor. Grant and Dweck (2003), did not find performance goals to be predictive but did demonstrated that mastery goals are predictive of performance in the context of undergraduate academics even when controlling for SAT score. Church et al. (2001) also find mastery goals to positively predict course performance. While the different findings for either performance (Elliot & McGregor, 2001; Elliot & Murayama, 2008) or mastery (Church et al., 2001; Grant & Dweck, 2003) may seem misaligned, we believe that investigating goals (1) alongside students' implicit theories, and (2) related to different outcomes (course performance and transfer) will help to reconcile the differences in findings.

Theories of Intelligence

While achievement goals have been shown to be predictive, they also arguably have antecedents (Bråten & Strømsø, 2004; Dweck & Master, 2009; Elliot & Church, 1997); initial learner dispositions that predict goals and that can be both measured and potentially manipulated. Students' theories of intelligence, the beliefs that students have about the nature of their own intelligence, are one of the most widely studied antecedents of achievement goals and have also been consistently studied for their own direct relationships to academic performance. Dweck and colleagues (Blackwell et al., 2007; Dweck, 2013; Dweck & Master, 2008; Henderson & Dweck, 1990) have found that learners' implicit theories of intelligence play a pivotal role in students' ability to perform intellectual tasks such as acquiring new knowledge or skills. Learners' theories of intelligence (TOI) fall along a continuum within two categories: incremental theory and entity theory. In incremental theory, students believe that their intelligence can be changed based on their efforts, whereas in entity theory, students believe that their intelligence is fixed and unchangeable. In general, those with incremental theories tend to acquire new knowledge or skills more readily, especially when completing challenging learning tasks (Dweck, 2013). These results indicate that incremental theorists should outperform entity theorists in classroom performance when accounting for other differences.

The advantage of incremental theory can be viewed through the framework of Vygotsky's (1978) theoretical construct of the Zone of Proximal Development (ZPD). For Vygotsky, the ZPD is the area between what a student can currently accomplish unaided and what a student cannot currently accomplish. The ZPD, then, contains content just beyond a student's current abilities, content that the student can master under guidance from either an adult or a more competent peer. While Vygotsky's definition relies on a human learning partner, it is arguable that a student can learn in the ZPD through other instructional content, such as a textbook or the Internet, either alongside or absent a human instructor. Azevedo and Hadwin (2005), for example, review a number of studies that demonstrate student learning through either instructional aids alone or the combination of aids and human instructors. For entity theorists, however, belief in a fixed intelligence leads them to prefer instructional content that is already within their level of current ability, avoiding the more difficult problems in the ZPD (Cury, Da Fonseca, Zahn, & Elliot, 2008; Dweck & Master, 2009; Hong, Chiu, Dweck, Lin, & Wan, 1999). The advantage for the incremental theorist is that, believing that their intelligence can be improved through effort, they are predisposed to choose more challenging items, problems, and content (Cury et al., 1999), voluntarily working in the ZPD and thus improving their abilities.

Relating TOI to Achievement Goals

In one of the earliest conceptions of a relationship between TOI and goals, Dweck (1986) predicted that entity theory would always lead to performance goals, whereas incremental theory would always lead to mastery goals. Elliot and McGregor (2001), however, found empirical evidence that students with entity theory are likely to hold avoidance goals, either mastery or performance, while students with incremental theory are unlikely to hold mastery avoidant goals, but may or may not be performance avoidant. They found no evidence of a relationship between students' TOI and approach goals.

One explanation, which begins to reconcile the difference between Dweck's predictions and empirical findings, is the addition of approach/avoidance distinction in the achievement goals framework. In Dweck's (1986) theoretical conception, entity theory should predict performance goals and performance goals should then predict either academic engagement or academic avoidance depending on "confidence in present ability" (p. 1041). Arguably, "confidence in present ability" is an aspect of the approach/avoidance axis of goal orientation with confident students manifesting an approach orientation and unconfident students manifesting avoidance. Given this conception, Dweck's predictions can be interpreted as (1) assuming an inherent approach/avoidance distinction, "confidence in present ability," and (2) assuming that approach/avoidance is an irrelevant distinction regarding mastery orientation. The proposed would agree with the former and challenge the latter, with the note that empirical data regarding mastery avoidance is minimal and mastery avoidance is not universally accepted as a component of achievement goals, with some researchers maintaining the tripartite model (Elliot, McGregor, & Gable, 1999; Pekrun et al., 2009; Richardson, Abraham, & Bond, 2012).

An Argument for Domain Specific Implicit Theories – Theories of Statistical Ability

Returning to the potential problem of domain generality in theories of intelligence, what if TOI are too general to be predictive in an undergraduate statistics context? The primary motivation for considering domain specificity in implicit theories stems from literature investigating domain specificity in mathematics (Alexander & Judy, 1998; Buehl, Alexander, & Murphy, 2002; Dweck, 2007; Schommer-Aikins, Duell, & Hutter, 2005). These investigations find that students do indeed hold domain specific mathematics beliefs, separable from their domain general beliefs. Buehl et al. (2002) conducted exploratory and confirmatory analysis of a domain specificity model, finding unique factors for the domain of mathematics and superior model fit for a four-factor domain specific model compared to a single-factor, domain general model. Alexander and Judy (1988) also find that students demonstrate use of both domain specific mathematics knowledge and domain general strategic knowledge when solving mathematics problems. While not directly arguing for a domain specific measure, Dweck's (2007) investigation of poor performance in girls with entity theory suggests that domain specific measures were used to assess students' beliefs about whether or not math ability is "a gift." While not directly related to mathematics, additional studies

(Hofer & Pintrich, 1997; Schommer & Walker, 1995) have also found support for the existence of both domain general and domain specific beliefs.

One way we predict that a domain specific measure will be beneficial is regarding Dweck's lack of predicted relationship between entity theory and mastery goals. This prediction seems logical only if TOI and goal orientation are measuring similar things. While achievement goal inventories are often measuring goals for a particular course or task, however, TOI instead measures theories of overall intelligence. It may be the case that students' TOI are or are not related to their goals depending on whether or not their conception of intelligence when responding to TOI questions matches their conception of achievement in the context under investigation.

Turning to statistics anxiety, we also see that while statistics anxiety predicts statistics performance, general anxiety is a much weaker predictor, when it is predictive at all. We argue that students' general TOI are likely to behave the same way when relating to statistics-specific outcomes, weakly predictive when they are predictive at all. Given such an argument, the current work sought to investigate whether or not a domain specific measure of *student theories of statistics ability* may be a stronger predictor of statistics performance than the more general TOI. Our motivation for this, beyond evidence for domain specificity in mathematics beliefs, is driven by two research findings: 1) Domain specific beliefs are uniquely predictive compared to domain general beliefs, and 2) Ability measures are uniquely predictive compared to intelligence measures. Regarding unique predictions, work by Bråten and Strømsø (2005) demonstrates that a number of personal epistemology measures, *speed of knowledge acquisition, certainty of knowledge*, and *knowledge construction and modification,* are both uncorrelated with theories of intelligence and uniquely predictive between students in different domains. Specifically, mastery goal orientation was predicted by teachers' ratings of speed of knowledge acquisition and of knowledge construction and modification, but by speed of knowledge acquisition and certainty of knowledge in business administration students. The control of knowledge acquisition measure, however, which was significantly correlated with theories of intelligence, was not predictive of mastery orientation in either group. Regarding ability versus intelligence, Bråten and Olaussen (1998) find that students' answers to a direct question about the malleability of intelligence are substantially different than their answers to conception of intelligence questions such as questions about the speed of learning and about reading comprehension. They also find that conception of intelligence is predictive of learning strategy use in incremental theorists even when controlling for domain general self-efficacy ratings. This result, while not directly utilizing domain specific conception of intelligence questions, suggests that *ability*, which is reflected in questions about learning speed and comprehension, may be a better unique predictor of performance when compared to *intelligence*.

Given the evidence that domain specific mathematics beliefs exist, that domain specific measures are uniquely predictive, and that ability-based predictors may outperform intelligence-based ones, the current work develops and tests a new inventory – theories of statistical ability (TOSA) – to assess whether it might serve as a better predictor of statistics performance than the domain-general TOI employed by Dweck and colleagues. Precedent for adapting TOI into an ability based measure has already been set by Chen and Pajares (2010) who created the Implicit Theories of Science Ability (ITSA) inventory in their path-model assessment of science achievement. They found that ITSA (both fixed and incremental) had a significant, albeit indirect, effect on achievement as well as being correlated with both achievement and self-efficacy, findings in line with our motivation for creating a similar measure in a statistics context.

Knowledge Transfer as a Performance Outcome

Definition and Relevance to Statistics Education

While course performance is the most recognized measure of academic outcomes, achieving knowledge transfer is perhaps more important if less widely understood. Transfer reflects that having knowledge in one area can aid problem solving in another area (Barnett & Ceci, 2002; Bransford & Schwartz, 1999; Gick & Holyoak, 1983; Holyoak & Thagard, 1989; Schwartz, Bransford, & Sears, 2005). One of the earliest notions of transfer, proposed by Gick and Holyoak (1983), is that of transfer as analogy. In this conception, a problem from one domain will act as an analogy to solving a problem presented in another domain. Analogy works by promoting schema induction, wherein each problem has a "problem schema" with an initial state, solution plan, and outcome. They find that transfer is greatest when the initial state, solution plan, and outcome of the analogy are all relevant to the target problem (complete analogy). For example, a story about needing to defeat a fortress maps completely to a problem regarding removing a tumor. Through reading the fortress story, a student should be much more able to solve the tumor problem than if they had not read the story. Because the analogous relationships map to those required to solve the target problem, the student transfers knowledge from one to the other. Gick and Holyoak (1983) also argue that the relationship between analogy and target problem need not be complete in order to promote transfer, which allows for a broader range of transfer applications. While transfer research has expanded since the initial work of Gick and Holyoak, the idea of structure mapping (Gentner, 1998; Gentner & Holyoak, 1997; Gentner & Markman, 1997; Holyoak & Thagard, 1995) still holds, wherein the core of transfer is the ability to use prior achievement to solve novel problems where prior achievement and novel problems share some similar underlying structures.

Transfer is also typically categorized by how related the prior achievement is to the target problem. The two categories of relatedness have been labeled in the literature as far and near transfer (Royer, 1986). Far transfer is similar to the transfer described by Gick and Holyoak (1983) and is characterized by the use of knowledge from one context to solve a problem occurring in a different context. Near transfer, conversely, is the transfer of knowledge from one context to a similar context (Barnett & Ceci, 2002). Contexts for transfer are defined in two different ways, domain and performance. Domain is the primary context investigated by Gick and Holyoak (1983) where domain is defined in terms of academic area (ex. history, biology, literature, etc.). Performance, however, is defined as the way in which the problem is solved (multiple choice, short answer, computation, essay, etc.). Based on the types of context, then, far transfer can be characterized either as between-domains or between-performance types (with near transfer defined as within either domain or performance type.) In terms of statistics education, transfer to a novel performance type is a desirable outcome for students completing an introductory statistics course. While course performance measures how well a student acquires and utilizes statistics content in an academic context, successful transfer would indicate that a student could take acquired statistics content and apply it to relevant “real world” problems, evidence of far transfer between performance types. In alignment with an interest in students’ abilities to successfully achieve far transfer, the distinguishing feature of the current study is that the target transfer problems were contextually unrelated to performance expectations within the statistics classroom, as explained in more detail below.

The definition of transfer in the current study, the use of domain-specific knowledge when solving real world problems, follows previous work on statistics transfer conducted by Daniel and Braasch (2013). In their study, they found that students who participate in real-world application exercises over the course of the semester are more likely to transfer statistics to a real-world context than those who do not engage in such exercises. The current study followed a procedure similar to the control condition used by Daniel and Braasch, focusing instead on the potential for individual differences to predict real-world transfer in the absence of other transfer promoting interventions.

Transfer as Related to Achievement Goals and Theories of Intelligence

While the relationship between learner characteristics and transfer has not been thoroughly studied as of yet, some studies have found significant relationships relevant to the proposed work. Belenky and Nokes-Malach (2013), for instance, find evidence that successful transfer is positively predicted by a mastery-approach orientation and may be negatively predicted by mastery-avoidance. Bransford and Schwartz (1999) suggest (although offer no statistical evidence for) a connection between transfer and theories of intelligence.

While few studies exist that link individual differences and transfer, we predicted a number of relationships based on theoretical assumptions. We first predicted that implicit theories should predict transfer in a way that mirrors course performance, with incremental theories positively predicting and entity theories negatively predicting transfer. Given the greater cognitive demands of transfer, however, we expected that implicit theories may be more weakly predictive of transfer than they are of course performance. While we expected that both TOI and TOSA would be weaker predictors of transfer, we anticipated that TOSA should predict more strongly than TOI, again mirroring expectations for course performance.

With respect to achievement goals, however, we anticipated that while mastery approach goals would be similar for both course performance and transfer, performance approach goals would differ between the two dependent variables. While both performance approach and mastery approach can predict course outcomes (Church et al., 1997; Elliot & McGregor, 2001; Elliot & Murayama, 2008; Grant & Dweck, 2003), Elliot and McGregor (2001) also find that performance and mastery reflect different study strategies that may relate to transfer even when they are not evident in course outcomes. Mastery goals, according to Elliot and McGregor's (2001) results, predict deep processing, a study strategy characterized by critically evaluating new information and attempting to integrate it with prior achievement and experience (Elliot, McGregor, & Gable, 1999, p. 549). Conversely, their results show that performance goals predict shallow processing, characterized by rote memorization and repetitive rehearsal of new information (Entwistle & Ramsden, 1983). As hypothesized by a number of studies (Belenky & Nokes-Malach, 2012; Belenky & Nokes-Malach 2013; Nokes-Malach & Mestre, 2013; Pugh & Bergin, 2006) the deep processing strategies predicted by mastery goals are likely to directly predict transfer, although no empirical studies depicting such a relationship have yet been conducted. Similarly, we anticipated a positive relationship between mastery approach and transfer, consistent with its anticipated relationship to course performance, and further hypothesized that mastery approach should have the strongest relationship to transfer of the four achievement goals.

While testing the direct relationship between study strategies and transfer was beyond the scope of the current study, we hypothesized that if deep processing should positively predict transfer then shallow processing should negatively predict. Given the demonstrated relationship (Elliot & McGregor, 2001) between shallow processing and performance approach, we anticipated an absent or negative relationship between performance approach and transfer. This was due to the assumption that while performance approach can positively predict course performance, its characteristic of shallow processing should hinder transfer ability, resulting in an absent or negative relationship. Regarding avoidance, we hypothesized that both avoidance goals would demonstrate an absent or a weak negative relationship to transfer.

Overview of the Current Study

In the current study, we investigated how achievement goals and theories of intelligence are associated with student success in an undergraduate statistics context as well as whether or not course performance and transfer performance are similarly or differentially predicted by achievement goals and implicit theories. Our purpose was to understand how learner characteristics relate to one another in a statistics classroom and to direct future undergraduate statistics studies and interventions. While the results of the current study serve as a replication for a number of published results (ex. Elliot &

McGregor, 2001; Belenky & Nokes-Malach, 2013), we also sought to address the following research questions:

(1) Is TOSA a stronger predictor of achievement goals than TOI?

(2) Is TOSA a stronger predictor of course outcomes (performance and transfer) than TOI?

(3) Do achievement goals behave similarly when predicting course performance and transfer?

(4) Can path models be statistically identified which describe how the interactions between achievement goals and implicit theories predict course performance and statistics transfer?

Method

Participants

Participants included college undergraduates from six sections of an introductory research and statistics course between Spring 2014 and Fall 2015. All enrolled students were eligible to participate, were compensated with course credit, and had the option of opting out of the study without penalty. Participants were excluded from the sample if they either formally or informally dropped the course prior to the final exam, resulting in approximately ten exclusions. For the full sample, not taking into account missingness (addressed in the plan for analysis), $N = 180$.

Materials

Achievement goals. The 12-item Achievement Goal Questionnaire developed by Elliot & McGregor (2001) was used as a measure of students' achievement goals. Composite scores for the four identified factors in Elliot and McGregor's two-by-two model of achievement were computed: performance approach, performance avoidance, mastery approach, and mastery avoidance. Elliot and McGregor find high reliability for all four factors, with Cronbach's alpha of .92, .83, .87, and .89, respectively. Example items include "It is important for me to do better than other students" for performance approach, "My goal in this class is to avoid performing poorly" for performance avoidance, "I want to learn as much as possible from this class" for mastery approach, and "I worry that I may not learn all that I possibly could in this class" for mastery avoidance. All items were rated on a Likert scale from 1 (not at all true of me) to 7 (very true of me).

Theories of intelligence and TOSA. To measure theories of intelligence, we used a recent version of Dweck's 8-item inventory, computing separate composite scores for the entity and incremental items (Dweck, 2013). Levy and Dweck (1997) have found good reliability for the 8-item inventory with alphas ranging from .93 to .95. The inventory includes incremental items such as "you can always substantially change how intelligent you are" and entity items such as "you can learn new things, but you can't really change your basic intelligence." TOSA was designed to mirror the TOI both conceptually and instrumentally to ensure the most accurate comparison possible to domain-general TOI ratings. Example items, which mirror the Dweck examples, are the incremental item "you can always substantially change your ability to solve statistical problems" and the entity item "you can learn new things, but you can't really change your basic ability to solve statistical problems." We computed TOSA, again mirroring TOI, by taking composite scores for incremental and entity with alphas of .88 and .86, respectively. Both inventories were rated on a Likert scale from 1 (strongly agree) to 6 (strongly disagree).

Prior achievement as a covariate. While not a variable of interest, we included students' self-reported GPA as a covariate to ensure that results were due to individual differences and not to prior achievement. While performance in a prerequisite math course would have been a superior prior achievement variable, as it is more related to statistics knowledge, data collected did not meet requirements for missing data (Enders, 2010) motivating a decision to include GPA, which did. While less relevant than prior math performance, GPA should be a sufficient covariate to ensure that results are not driven solely by prior achievement. The demonstrated relationship between GPA, course performance, and transfer, also indicated that it was a relevant prior achievement covariate.

Course materials and the measurement of course performance and attendance. Course materials included lectures, Keynote slides (presented in class and provided electronically to students), daily quizzes, labs, study guides, take-home homework including computational problems, and exams. All course materials were based on *Research Methods and Statistics: A Critical Thinking Approach* (Jackson, 2011, 2015). While both composite exam grade and final grade were considered as measures of course performance, final grade was chosen given more appropriate distribution of scores and fewer univariate outliers. Final grade was computed as a composite of the following: quiz scores, which also reflect attendance (failure to attend results in a zero quiz grade), literature search and SPSS labs, exam scores, and extra credit, including both in-class and take-home assignments. Exams included a combination of multiple choice items, both from the textbook's test bank and instructor created, short answer essay questions, and statistical computations such as computing a Pearson's product moment correlation by hand. Given that we will not analyze the role of attendance in the present study, the inclusion of attendance related measures in the final grade composite will not be a concern.

Assessment of transfer. Transfer was assessed through coding students' open-ended responses to four target questions. The target questions were administered as part of a nine question task presented as a course survey from the Psychology Department. Survey packets were designed with university and departmental branding. The context of the task, further elaborated in the procedure in which the task was administered (see below), was designed to guard against artificial transfer effects, where students would be motivated to transfer because they were stimulated by a statistics context or because they were unconvinced by the ruse of the task. While two of the items in the task were in fixed-positions, the remaining items were presented in six semi-random orders to guard against order effects, where the order of the items themselves might either stimulate transfer or stimulate other order-based artifacts in responses.

The target items retained were worded to target statistics concepts covered in the course including correlation versus causation, ordinal versus interval data, the problem with quasi-experimental or self-selecting samples, the problem of third variables, and the importance of sample size and standard deviation. All items were scored on a zero to two scale, with the following criteria: (0) No evidence of statistics transfer. Response may show lay understanding of research methods concepts, but does demonstrate any understanding of target concepts. (1) Minimal evidence of statistics transfer. Response mentions appropriate concerns regarding the target concepts but demonstrates minimal understanding. (2) Demonstrates evidence of transfer. Response applies accurate statistics and research methods knowledge learned from the course to address the questions asked. Two raters scored all participant responses, with disagreements resolved through discussion. Inter-rater reliability, calculated using Cohen's kappa, was $\kappa = .88$. Transfer scores for each participant were treated as a composite of scores on each of the four items, for a possible range of zero through eight. Actual scores, however, ranged from zero through six, indicating that no students achieved full transfer on all target items. Transfer scores were low overall, with between 61 and 91% of participants showing no evidence of transfer, depending on the target item. Full text for each of the four items is included, with target concepts and score distribution, in Appendix A.

Procedure

Students completed all individual differences inventories between weeks 6 and 7 during the semester. The three statistics exams that constitute course performance were administered during weeks 5, 11, and 18. The transfer task was administered during the final two weeks of class in an alternate classroom across the hall from their regular statistics classroom. The task was administered by a staff member from the Psychology Department's Academic Advising Resource Center (AARC) to guard against artificial transfer effects and was presented by the AARC administrator as a survey from the Department.

Plan for Analysis

The following analyses were planned to address research questions: For question (1) is TOSA more closely related to achievement goals than TOI, bivariate correlations were conducted and compared. For question (2) is TOSA a stronger predictor of course outcomes than TOI, four hierarchical regressions were conducted. Each of the four regressions included self-reported GPA in Step 1 in order to remove variance due to prior achievement. The first set of regressions tested final grade and transfer respectively as outcome variables including TOSA entity, TOSA incremental, TOI entity, and TOI incremental as predictors in Step 2. For the second regression, only TOSA entity and TOSA incremental were included. Thus, the first set of regressions assess whether or not TOSA is a stronger predictor than TOI and the second set assess whether or not TOSA is a significant predictor when TOI is removed from the model. For question (3) do achievement goals behave similarly when predicting course performance and transfer, two hierarchical regressions were conducted, one for final grade and one for transfer, including self-reported GPA as a covariate in Step 1 and the four achievement goals variables in Step 2. For questions (2) and (3) final grade analyses were conducted using linear regression. Transfer analyses, however, were conducted using logistic regression as described below. For question (4) identifying path models, four models of final grade and four models of transfer were analyzed and compared. Comparisons were made separately for the four final grade models and the four transfer models.

Prior to conducting any analyses, data were screened in SPSS 23 to address issues of missingness, normality, and univariate outliers, following recommendations by Pallant (2013) and Tabachnick and Fidell (2007). Missingness was found on two variables, self-reported GPA and transfer. GPA was missing for seven participants, resulting in 3.9% missingness and transfer was missing for nine participants, resulting in 5% missingness. In both cases, amount of missingness is small and appears to be missing at random (MAR.) Missing cases were excluded list-wise from relevant analyses and total n is reported by variable for correlations and by analysis for regressions to address when participants were and were not excluded.

To meet regression assumptions, only the outcome variables, final grade and transfer, needed to demonstrate evidence of normality or be transformed prior to analysis. Final grade met normality assumptions as initially calculated (as did self-reported GPA, indicating a similar distribution to final grade), but transfer scores did not. While not necessary for analysis, it is worth noting that no individual differences scores met normality assumptions. There is some reason to believe that response bias was playing a role in individual differences responses, which will be addressed in more detail below.

Because transfer was not amenable to log transformations to resolve issues of non-normality, we created a binary transfer score, Transfer A, in order to pursue logistic rather than linear regression for transfer analyses. Transfer A was created by recoding composite scores of zero (no transfer on any item) and one (partial transfer on a single item) as 0 in the dichotomous variable. Composite scores of two (full transfer on a single item or partial transfer on two items) or more were coded as a 1 in the dichotomous variable. This is a more conservative approach than coding all non-zero scores as 1 and conceptually represents little to no transfer evident (0) or some transfer evident (1). Transfer A included 115 cases (67%) demonstrating little to no transfer evident and 56 cases (33%) demonstrating some transfer evident.

Finally, data were screened for univariate outliers, with outliers found on a number of variables including final grade and individual differences measures. For final grade, outliers were present on the low end and were resolved by adjusting outlier "F"s towards the mean. For individual differences, outliers were also adjusted towards the mean resulting in no more than a .5 change in composite score. In both cases, outlier resolution follows procedures recommended by Tabachnick and Fidell (2007).

For regression analyses, multivariate outliers and multi-collinearity were also addressed. In several instances, multivariate outliers were identified based on an evaluation of Mahalanobis distances after regression was conducted. In each instance, the number of outliers was no more than five cases. After removing multivariate outliers and rerunning analyses, regressions produced similar results but also produced additional offending Mahalanobis values. Given similarity of results, and given that multivariate outliers could be driven by our suspicion of response bias, only initial regression results are reported, with the caveat that some multivariate outliers do appear to be present. For multi-collinearity, VIF and tolerance values were screened for VIF above 10 or tolerance below .10, either of which would indicate the presence of problematic multi-collinearity (Pallant, 2013). VIF and tolerance are presented for TOI/TOSA only, as achievement goals did not display high enough inter-correlation to warrant a review of multi-collinearity. While VIF and tolerance are not available for logistic regression, acceptable values in linear regression indicate that multi-collinearity should also be acceptable in logistic analyses given inclusion of the same predictor variables in both models.

For path analysis, all models were evaluated in MPlus 7.4. For course performance analyses, maximum likelihood estimation was used given normality in the final grade variable. For transfer, analyses were conducted using maximum likelihood estimation with robust standard errors (MLR), an estimation method that robust to non-normality. Using MLR, we were able to test the models with the originally specified transfer composite scores, which offer a fuller picture of transfer than the re-specified binary coding. Both types of maximum likelihood estimation, when utilized in Mplus, also estimate missing data using full-information maximum likelihood (FIML.) Given appropriate estimations for missingness, all participants are included in path analysis and N = 180 for all path models.

For course performance, we tested the following models: Model A, consistent with Elliot and McGregor (2001) (Figure 1), Model B, consistent with Dweck's (1986) assumptions (Figure 2), and Model C, a theoretical model eliminating direct relationships between implicit theories and course performance outcomes (Figure 3). We also tested Models A1 through C1, which mirror Models A-C replacing TOI with TOSA. All path analysis figures use pluses and minuses to depict the direction of hypothesized relationships.

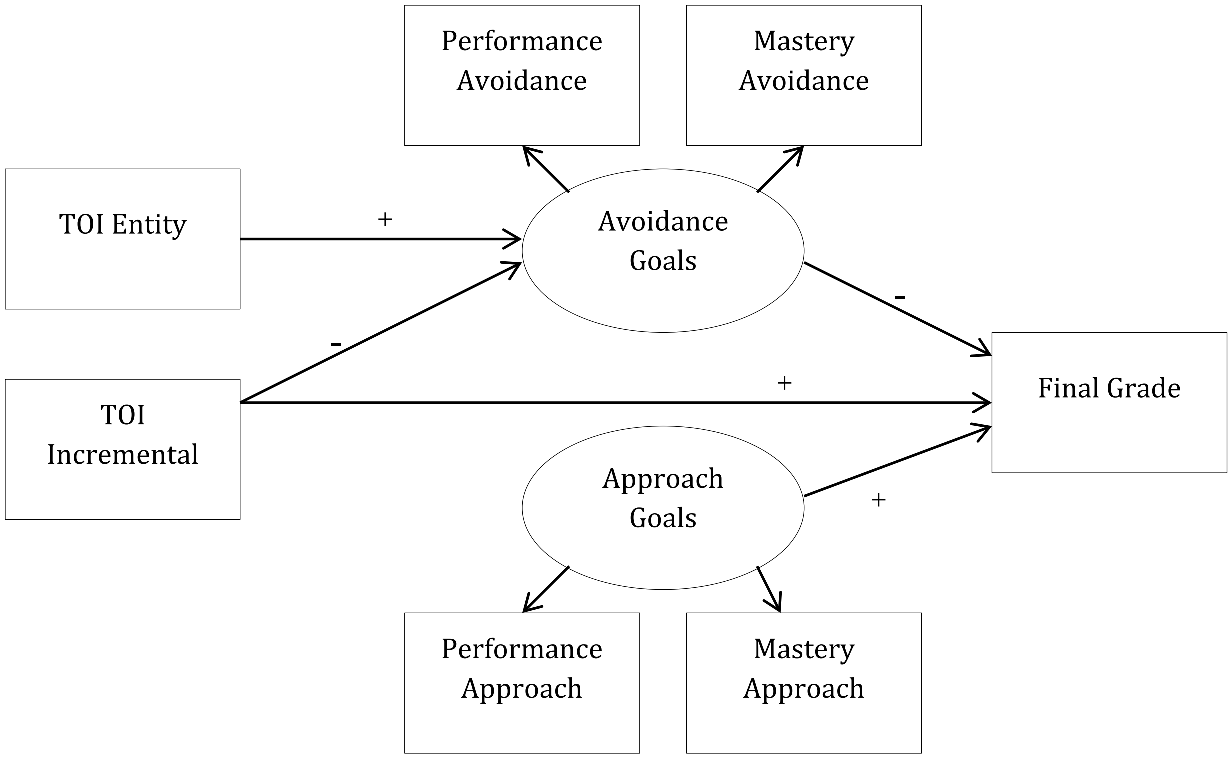

Figure 1. Model A. TOI and Avoidance/Approach Goals predict Final Grade. (Model A1 replaces TOI with TOSA.)

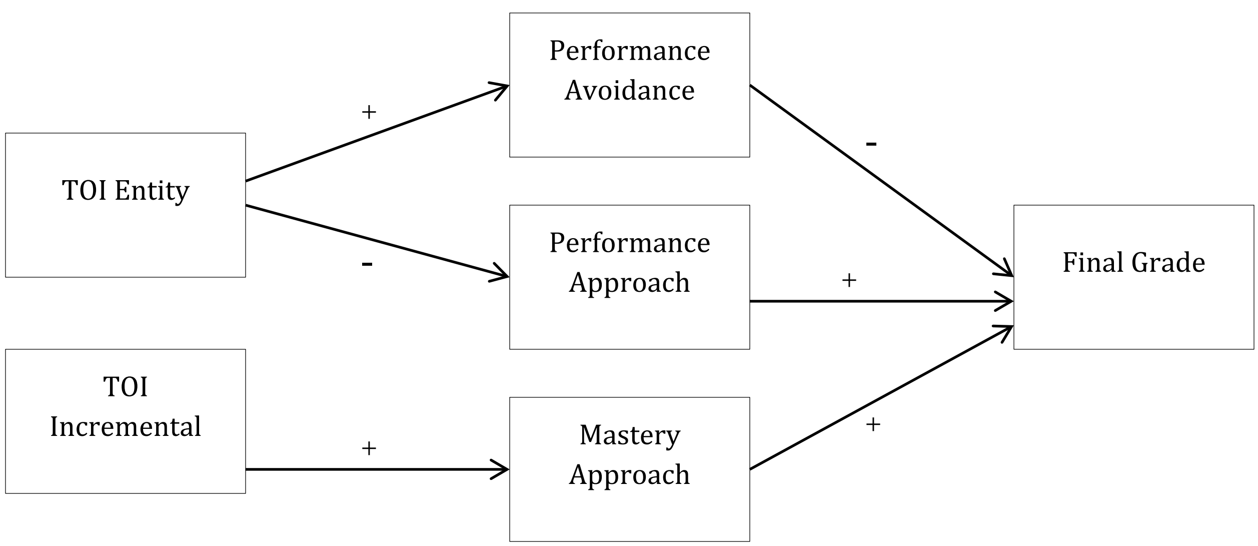

Figure 2. Model B. TOI, Performance Goals, and Mastery Approach predict Final Grade. (Model B1 replaces TOI with TOSA.)

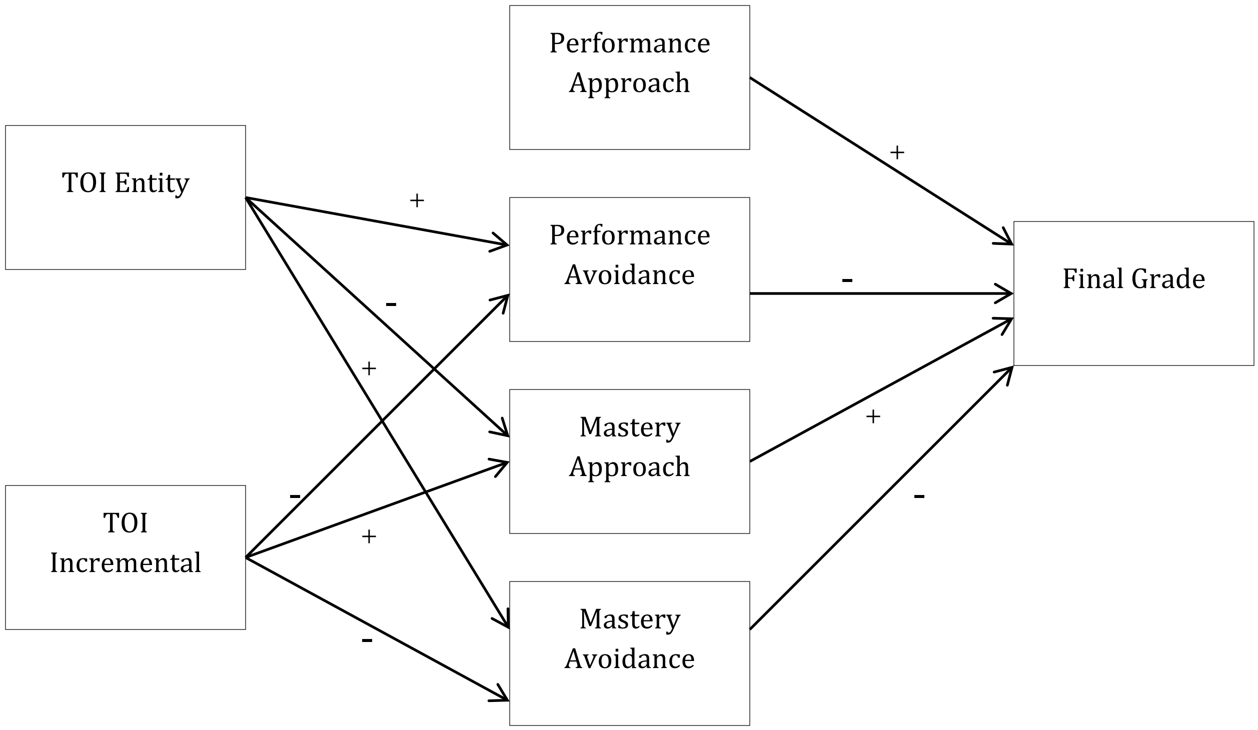

Figure 3. Model C. TOI and Achievement Goals Predict Statistics Course Performance. (Model C1 replaces TOI with TOSA.)

For transfer, we tested the following models: Model D, a variation of Model A which breaks approach goals into mastery and performance (Figure 4), Model E, which mirrors Model B but with a change in valence expectation for performance approach (Figure 2), and Model F, which mirrors Model C again with a change in valence for performance approach (Figure 3), and Models D1 through F1, which mirror Models D-F and replace TOI with TOSA. Our only predicted change from performance to transfer is the change in valence for performance approach expectations for all models.

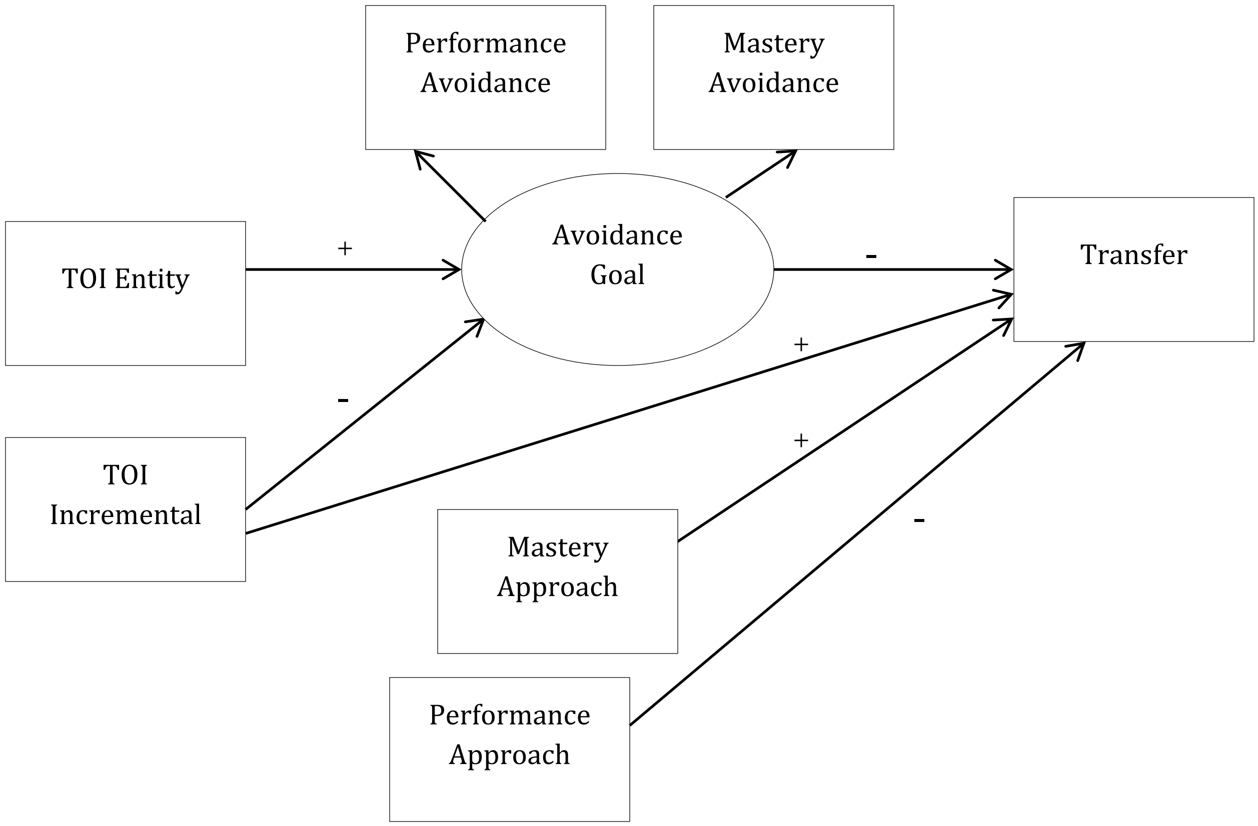

Figure 4. Model D. TOI and Avoidance/Approach Goals predict Transfer. (D1 replaces TOI with TOSA.)

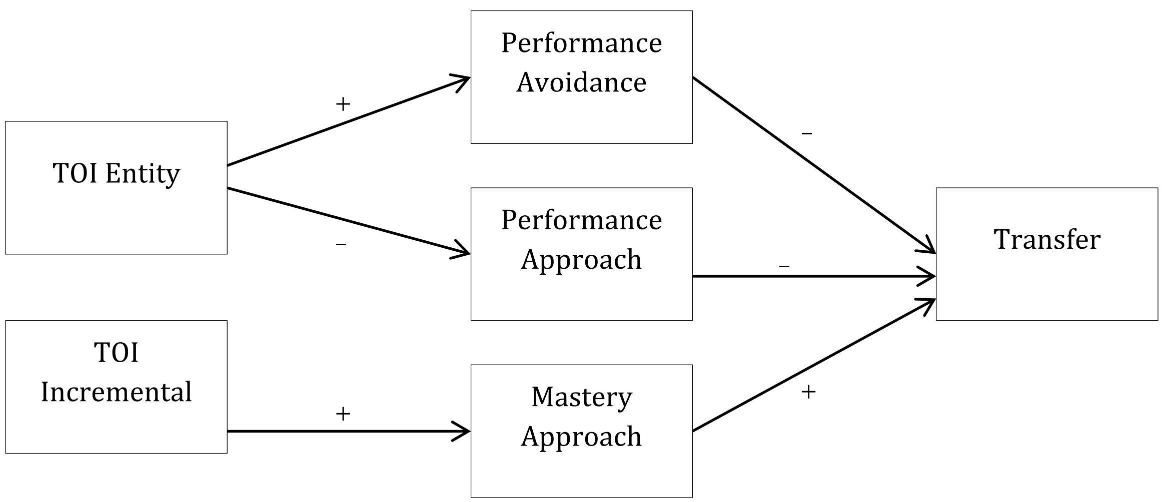

Figure 5. Model E. TOI, Performance Goals, and Mastery Approach predict Transfer. (E1 replaces TOI with TOSA.)

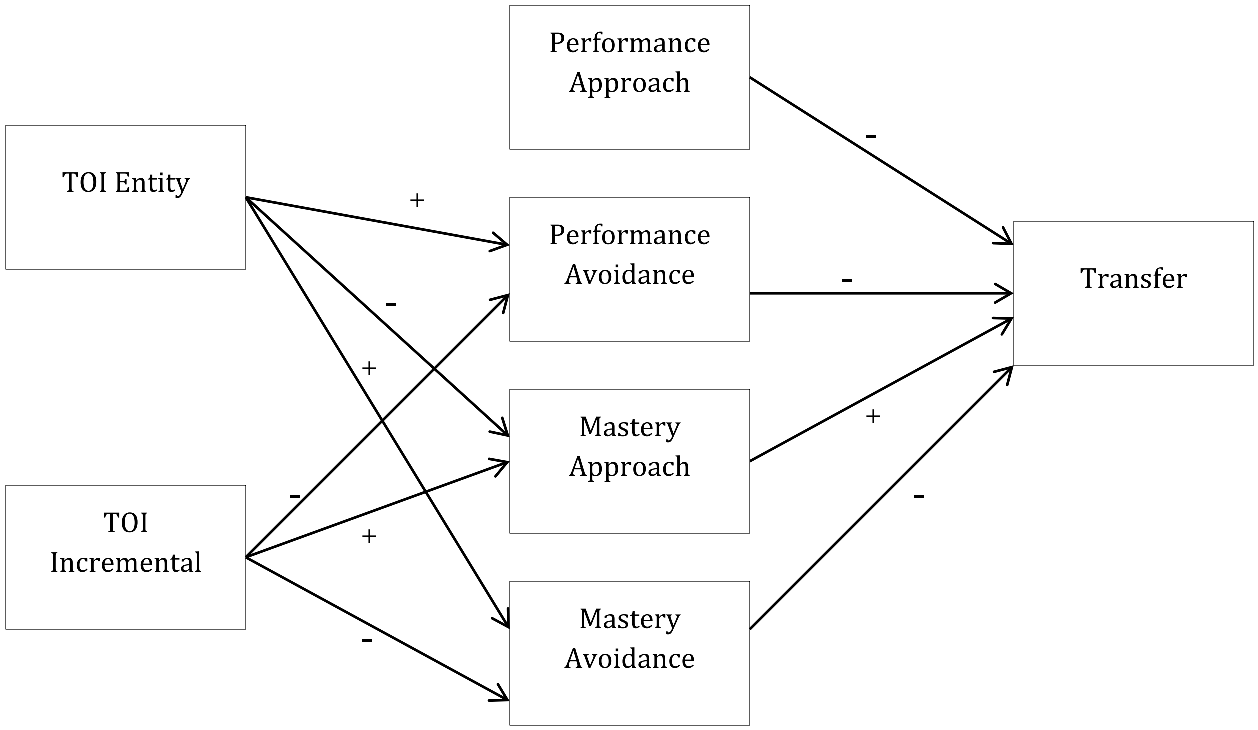

Figure 6. Model F. TOI and Achievement Goals predict Transfer. (F1 replaces TOI with TOSA.)

Models were first evaluated individually based on the following fit statistics, as recommended by Kline (2011): Model Chi-square, Steiger-Lind root mean square error of approximation (RMSEA), Bentler comparative fit index (CFI), and standardized root mean square residual (SRMR). Model χ^2 is a badness of fit index, measuring how much the predicted model deviates from the sample values. A significant χ^2 indicates significant difference between the model and the data, indicating lack of fit. While χ^2 can become significant in large samples that otherwise demonstrate good fit, it should be non-significant in the current study given the relatively small sample size. RMSEA is also a badness of fit index, with recommended values of less than .05 for good fit and between .05 and .08 for adequate fit, ideally including the upper confidence interval, with values greater than .10 indicating inadequate fit (Browne, Cudeck & Bollen, 1993). The CFI is a goodness of fit index with values of greater than .90 indicating adequate fit and values of greater than .95 indicating excellent fit (Hu & Bentler, 1999). The SRMR is also a goodness of fit index with values of less than .10 indicating adequate fit and values of less than .08 indicating a good fit (Hu & Bentler, 1999). For model comparison, the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC) were compared between adequately fitting models, with preference going to models with the lowest AIC and BIC values (West, Taylor, & Wu, 2012).

Results

Question 1: Is TOSA a Stronger Predictor of Achievement Goals than TOI?

Our first goal was to investigate the relationship between achievement goals and implicit theories of intelligence (TOI) and statistical ability (TOSA). Bivariate correlations for these, as well as all other variables, are reported in Table 1. Before reviewing correlations with implicit theories, it is worth noting that achievement goals themselves have unanticipated inter-correlations. We anticipated that mastery and performance approach would be positively correlated, mastery and performance avoidance would be positively correlated, and that approach goals would be inversely correlated with avoidance goals. Consistent with predictions, mastery approach and performance approach were positively correlated (r =.25, p <.01), and mastery avoidance and performance avoidance were also positively correlated (r = .34, p <.01.) Contrary to predictions, however, there was no significant relationship between performance approach and mastery avoidance (r =-.05, p -.53) and there was a small positive correlation between mastery approach and performance avoidance (r = .19, p <.05) rather than the negative correlation that was expected.

Table 1

Correlations between Individual Differences and Outcomes

Variable	1	2	3	4	5	6	7	8	9	10	11
1. Performance Approach	-	.020	.250**	-.047	.062	-.051	.054	-.054	.168*	.024	.070
2. Performance Avoidance	-	-	.192*	.344**	.114	-.050	.141	.011	-.096	-.027	-.294**
3. Mastery Approach	-	-	-	-.009	.117*	-.156*	.235**	-.260**	.231**	.067	.003
4. Mastery Avoidance	-	-	-	-	-.057	.126	-.116*	.204**	-.155*	-.125	-.132
5. Incremental TOI	-	-	-	-	-	-.740**	.629**	-.523**	-.004	-.046	-.178*
6. Entity TOI	-	-	-	-	-	-	-.510**	.542**	-.017	.034	.158*
7. Incremental TOSA	-	-	-	-	-	-	-	-.765**	.123	.078	-.113
8. Entity TOSA	-	-	-	-	-	-	-	-	-.212**	-.088	-.014
9. Final Grade	-	-	-	-	-	-	-	-	-	.559**	.262**
10. GPA	-	-	-	-	-	-	-	-	-	-	.224*
11. Transfer A	-	-	-	-	-	-	-	-	-	-	-
M	4.54	5.73	5.90	4.17	4.48	2.36	4.69	2.26	.85	3.13	.33
SD	1.71	1.04	.97	1.52	1.04	1.00	.89	.82	.11	.51	.47
Valid N (listwise)	180	180	180	180	180	180	180	180	180	173	171

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

Counter to predictions that both TOI variables would be related to all achievement goals variables, TOI was only significantly related to mastery approach, albeit in the predicted directions. TOI entity was negatively related to mastery approach (r = -.16, p <.05) and TOI incremental was positively related to mastery approach (r =.12, p <.05.) TOSA relationships also ran counter to predictions (that both TOSA variables would relate to all achievement goals), however TOSA was significantly related to mastery avoidance in addition to mastery approach, all in the predicted directions. TOSA entity demonstrated a negative relationship with mastery approach (r = -.26, p <.01) and a positive relationship with mastery avoidance (r =.20, p <.01) while TOSA incremental displayed relationships in the opposite direction (r = .24, p <.01 for mastery approach; r = -.17, p <.05 for mastery avoidance.) While neither performance variable displayed significant relationships with either TOI or TOSA, it is worth noting that, similar to its strange relationship with mastery approach, performance avoidance is also demonstrating potential for a positive relationship with incremental TOSA (r =.14, p =.06.)

Question 2: IS TOSA a Stronger Predictor of Course Outcomes than TOI?

Our second goal was to investigate how implicit theories predict both final grade and transfer, as well as whether or not TOSA is a stronger predictor of either. We first conducted hierarchical linear regression on final grade including both TOI and TOSA in Step 2, with results presented in Table 2. Notably, change in R^2 was not significant (F (4, 167) = 2.23, p = .07) when adding both TOI and TOSA together into the regression model at Step 2. Despite non-significant R^2 change, however, the model does indicate that TOSA Entity is the only significant predictor of final grade in Step 2.

Table 2

Hierarchical Regression Analysis of Implicit Theories predicting Final Grade after Controlling for Self-reported GPA

Variable	*B*	SE *B*	β	*t*	R^2	ΔR^2	Tol	VIF
Step 1					.31	.31	1.00	1.00
Self-reported GPA	.12	.01	.56	8.82***				
Step 2					.35	.04		
Self-reported GPA	.12	.01	.54	8.51***			.98	1.03
TOI Entity	.01	.01	.04	0.41			.41	2.43
TOI Incremental	-.01	.01	-.04	-0.39			.36	2.79
TOSA Entity	-.04	.01	-.27	-2.61**			.38	2.66
TOSA Incremental	-.01	.01	-.08	-0.71			.34	3.00

*Note. Tol = tolerance. N = 173. **p < .01. ***p < .001.*

Next, we conducted hierarchical regression including only TOSA variables in Step 2, as presented in Table 3. In this model, TOSA does contribute significantly to the regression model (F (2, 169) = 4.07, p <.05) although it only explains 3% of the variance in final grade. TOSA Entity is still the only significant predictor in Step 2.

Table 3

Hierarchical Regression Analysis of Theories of Statistical Ability predicting Final Grade after Controlling for Self-reported GPA

Variable	*B*	SE *B*	β	*t*	R^2	ΔR^2	Tol	VIF
Step 1					.31	.31		
Self-reported GPA	.12	.01	.56	8.82***			1.00	1.00
Step 2					.34	.03		
Self-reported GPA	.12	.01	.55	8.73***			.99	1.01
TOSA Entity	-.03	.01	-.25	-2.55**			.41	2.42
TOSA Incremental	-.01	.01	-.11	-1.12			.41	2.42

*Note. Tol = tolerance. N = 173. **p < .01. ***p < .001.*

Moving to transfer analyses, we first conducted hierarchical logistic regression on transfer including both TOI and TOSA in Step 2, with results presented in Table 4. Overall, the full model was statistically significant, chi-square (4, N = 164) = 19.76, p <.05, indicating that the model was able to distinguish between little to no transfer and evidence of transfer. The entire model explained between 11% (Cox & Snell R^2) and 16% (Nagelkerke R^2) of the variance in transfer and correctly classified 73% of cases. As with final grade, results indicate that TOSA entity is the only significant predictor of transfer after controlling for self-reported GPA, with an odds ratio of .42. The odds ratio indicates a small effect, however, indicating that for every additional point decrease on TOSA entity an individual is .42 times more likely to show evidence of successful transfer.

Table 4

Hierarchical Logistic Regression Analysis of Implicit Theories predicting Transfer Likelihood after Controlling for Self-reported GPA

Variable	*B*	SE *B*	Wald	df	Odds Ratio	95% C.I.	
						Lower	Upper
Step 1							
Self-reported GPA	1.00	.36	7.89**	1	2.71	1.35	5.44
Step 2							
Self-reported GPA	1.00	.38	7.12**	1	2.72	1.30	5.67
TOI Entity	.35	.28	1.52	1	1.42	.81	2.48
TOI Incremental	-.12	.29	.18	1	.89	.50	1.57
TOSA Entity	-.86	.38	5.04*	1	.42	.20	.90
TOSA Incremental	-.64	.36	3.20	1	.53	.26	1.06

Note. $N = 164$. $*p < .05$. $**p < .01$.

Next, we again conducted hierarchical logistic regression including only TOSA variables in Step 2 as presented in Table 5. In this model, TOSA entity loses significance as a predictor and TOSA incremental becomes a significant negative predictor, a result that directly opposes expected results. Overall, however, the full model was statistically significant, chi-square (2, N = 164) = 15.35, p <.05, indicating that the model was able to distinguish between little to no transfer and evidence of transfer. The entire model explained between 9% (Cox & Snell R^2) and 13% (Nagelkerke R^2) of the variance in transfer and correctly classified 71% of cases.

Table 5

Hierarchical Logistic Regression Analysis of TOSA predicting Transfer Likelihood after Controlling for Self-reported GPA

Variable	*B*	SE *B*	Wald	df	Odds Ratio	95% C.I.	
						Lower	Upper
Step 1							
Self-reported GPA	1.00	.36	7.89**	1	2.71	1.35	5.44
Step 2							
Self-reported GPA	1.09	.37	8.57**	1	2.96	1.43	6.12
TOSA Entity	-.67	.35	3.54+	1	.52	.26	1.03
TOSA Incremental	-.79	.32	6.30*	1	.45	.24	.84

*Note. N = 164. *p <.05. **p < .01. +p=.06.*

Question 3: Achievement Goals Predicting Final Grade and Transfer

Our third goal was to understand whether or not achievement goals are significant predictors of either final grade or transfer, as well as whether or not they differentially predict the two outcomes. We first conducted hierarchical linear regression on final grade including all achievement goals in Step 2, with results presented in Table 6. Introducing achievement goals into the model at Step 2 did result in a significant change in R^2 (F (4, 167) =4.37, p <.01) and explained an additional 7% of the variance in final grade. Of the individual achievement goals, however, only mastery approach was a significant predictor of final grade.

Table 6

Hierarchical Regression Analysis of Achievement Goals predicting Final Grade after Controlling for Self-reported GPA

Variable	*B*	SE *B*	β	*t*	R^2	ΔR^2
Step 1					.31	.31
Self-reported GPA	.12	.01	.56	8.82***		
Step 2					.38	.07
Self-reported GPA	.12	.01	.54	8.68***		
Performance Approach	.01	.00	.11	1.71		
Performance Avoidance	-.01	.01	-.10	-1.55		
Mastery Approach	.02	.01	.19	2.90**		
Mastery Avoidance	.00	.01	-.05	-0.71		

Note. $N = 173$. $^{**}p < .01$. $^{***}p < .001$.

Next, a two-step hierarchical logistic regression was conducted to investigate the predictive relationship between achievement goals and transfer with results presented in Table 7. Overall, the full model was statistically significant (chi-square (5, N = 164) = 24.58, p <.05), explained between 14% (Cox & Snell R^2) and 19% (Nagelkerke R^2) of the variance in transfer, and correctly classified 74% of cases. Despite model significance, however, performance avoidance was the only statistically significant achievement goals predictor after controlling for GPA. The size of the odds ratio indicates a small effect, however, with an individual being .52 times more likely to show evidence of successful transfer given a one point decrease on performance avoidance.

Table 7

Hierarchical Logistic Regression Analysis of Achievement Goals predicting Transfer Likelihood after Controlling for Self-reported GPA

Variable	*B*	SE *B*	Wald	df	Odds Ratio	95% C.I.	
						Lower	Upper
Step 1							
Self-reported GPA	1.00	.36	7.89**	1	2.71	1.35	5.44
Step 2							
Self-reported GPA	1.02	.37	7.50**	1	2.77	1.34	5.73
Performance Approach	.11	.11	.91	1	1.11	.89	1.39
Performance Avoidance	-.66	.19	12.23***	1	.52	.36	.75
Mastery Approach	.09	.19	.22	1	1.10	.75	1.60
Mastery Avoidance	.01	.13	.00	1	1.00	.79	1.29

*Note. N = 164. **p < .01. ***p < .001.*

Question 4: Path Models of Achievement Goals and Implicit Theories Predicting Final Grade and Transfer

In path model analysis, we first conducted model testing on models A-C and A1-C1 to determine goodness of fit for models predicting final grade, with results presented in Table 8. Model A was the only original model to demonstrate potential for adequate fit, although neither RMSEA nor CFI produced truly appropriate values based on recommendations.

Table 8

Path Models Predicting Final Grade: Fit Statistics for Models A-C and Models A1-C1

Model	χ	RMSEA [90% CI]	CFI	SRMR	AIC	BIC
A	17.54	.07 [.00, .11]	.86	.06	2995.11	3074.93
B	20.14**	.09 [.04, .14]	.58	.06	1457.07	1401.77
C	41.93***	.15 [.11, .20]	.38	.08	1415.26	1472.74
A1	Failure to converge					
B1	35.98***	.14 [.10, .19]	.43	.08	1452.90	1497.60
C1	48.02***	.17 [.12, .21]	.50	.08	1396.58	1454.05

Note. *p <.05. **p < .01. ***p < .001.

Modification indices for Model A, however, indicated that removing performance avoidance might also improve model fit. Models A and A1 were re-specified dropping performance avoidance with fit indices for both presented in Table 9. Of the two respecified models, only Model A showed acceptable fit. Despite acceptable fit, however, only approach and mastery avoidance demonstrated significance when predicting final grade. Based on unstandardized estimates, a one point increase in approach would result in a .08 increase in final grade while a one point decrease in mastery avoidance would result in a .01 increase in final grade, each holding all other variables in the model constant. R^2 for final grade was also significant with the whole model explaining 18% of the variance in final grade.

Table 9

Re-specified Path Models for A & A1, Removing Performance Avoidance

Model	X^2	RMSEA [90% CI]	CFI	SRMR	AIC	BIC
A	6.43	.00 [.00, .09]	1.00	.05	2485.51	2549.37
A1	18.18*	.09 [.04, .15]	.73	.08	2338.66	2402.52

Note. *p <.05. **p < .01. ***p < .001.

Next, we conducted model testing on models D-F and D1-F1 to determine goodness of fit for models predicting transfer, with results presented in Table 10. Model D was the only transfer model to demonstrate potential goodness of fit with a non-significant X^2, albeit slightly less than adequate CFI and poor fit indicated by the upper CI of the RMSEA. Despite tentative support for Model D, however, TOI incremental was a significant negative predictor of transfer, with unstandardized estimates predicting a .18 increase in transfer for every one-point decrease in TOI incremental. Given marginal model fit and lack of appropriate relationships, no model is retained for transfer.

Table 10

Path Models Predicting Transfer: Fit Statistics for Models D-F and Models D1-F1

Model	X^2	RMSEA [90% CI]	CFI	SRMR	AIC	BIC
D	11.89	.06 [.00, .12]	.88	.04	1756.26	1800.97
E	24.27**	.11 [.06, .16]	.51	.07	2320.57	2365.27
F	46.57***	.16 [.12, .21]	.29	.09	2280.76	2338.24
D1	24.88***	.12 [.07, .17]	.67	.06	1750.46	1795.17
E1	35.61***	.14 [.09, .19]	.42	.07	2315.40	2361.10
F1	46.90***	.16 [.12, .21]	.47	.08	2262.08	2319.56

Note. *$p < .05$. **$p < .01$. ***$p < .001$.

Discussion

Review of Findings

Overall, results provided some support for predictions and a number of relevant conclusions can be drawn based on the data. In line with predictions, TOSA was a stronger predictor of achievement goals than TOI. While neither was related to performance goals, TOSA entity was negatively correlated with mastery approach and positively correlated with mastery avoidance. TOSA incremental correlated with mastery approach and avoidance in the opposite directions. TOI only correlated with mastery approach, and weaker than TOSA. TOSA was also a better predictor of course performance and transfer, with TOSA entity emerging as the only significant predictor of the TOSA and TOI variables, negatively predicting both course performance and transfer, albeit less conclusively for transfer if TOI is removed from the regression model. Achievement goals additionally supported our hypotheses, with mastery approach positively predicting course performance and performance avoidance negatively predicting transfer. Results of path analysis were inconclusive but do tentatively support an approach/avoidance distinction of achievement goals. These conclusions are relevant both in terms of their relationship to previous research and their implications for future directions, although they do have a number of limitations, as discussed below.

Conclusions, Limitations, and Future Directions

Conclusion 1: TOSA is a stronger predictor of achievement goals than TOI. While the relationship between achievement goals and implicit theories was not as evident as anticipated, results do provide some replication support of prior research. Inconsistent with the findings of Elliot & McGregor (2001), TOI was not related to either performance or mastery avoidance, but was related to mastery approach, with entity negatively predicting and incremental positively predicting. This is also inconsistent with Dweck's (1986) original conception theorizing a relationship between entity theory and performance goals. When comparing achievement goals to TOSA, however, we do see evidence of Dweck's conception of the relationship with incremental theory and mastery, with a positive relationship evident between TOSA incremental and mastery approach. This supports our hypothesis that a domain specific measure of statistics ability is able to capture mastery goals in a way that TOI is not. Also consistent with hypotheses, TOSA incremental is negatively related to mastery avoidance and TOSA entity is positively related to mastery avoidance while negatively related to mastery approach. As with TOI, however, TOSA did not demonstrate a relationship with performance goals. One reason for this lack of relationship, of course, may be that it does not exist in this context, contrary to prior theory and results. Another reason, however, might be related to response bias in the TOSA inventory or factoring issues within the achievement goals inventory. The issue of response bias is revisited when discussing TOSA predicting final grade.

Aside from relating to previous research, results also support the hypothesis that a domain specific measure of statistics ability was more closely related to students' achievement goals than a domain general measure of intelligence. Future studies that wish to investigate both achievement goals and implicit theories in a classroom setting might consider an implicit theories measure that is tied to the classroom domain rather than measuring intelligence more generally. Future research might also consider whether or not a domain specific measure of achievement goals similarly strengthens the relationship between theories and goals. While TOI seems to be too domain general, the achievement goals inventory may be too specific, focusing on students achievement goals in the specific class rather than in the domain of the course. Class-specific achievement goals responses might be sensitive to class makeup, instructor, and context of administration (e.g. before or after an exam), in a way that does not truly capture how the student is interacting within the domain.

Conclusion 2: TOSA is a stronger predictor of course outcomes than TOI. Turing to implicit theories as a predictor, results showed support for our hypothesis that a domain specific abilities measure will out predict a domain general intelligence measure when predicting course performance. Of the two inventories, TOI regressions demonstrated very small beta weights as well as lack of significance. While TOSA incremental did not predict increases in final grade, TOSA entity was a significant negative predictor and the only significant predictor in an implicit theories regression model. While the relationship between TOSA entity and final grade was small, its existence in comparison to null TOI results is enough to suggest the efficacy of a domain specific measure. Arguably, the lack of relationship between TOSA incremental and final grade could also be a true result, indicating something about the way an incremental theory operates in terms of undergraduate outcomes. The belief in being able to improve one's statistics ability through effort does not guarantee that a student will actually expend that effort. A lack of significant incremental results may be reflective of that fact, especially in an undergraduate context where elements beyond classroom efficacy (such as availability of parties and alcohol, competing commitments such as employment and family, etc.) are more influential on course engagement than they are in K-12.

Results might also, however, be due to participant response bias. Regarding response bias, procedures for this study involved administering individual differences in the statistics classroom with the instructor present. While students were assured that their responses were confidential and anonymous, the environment and presence of instructor could have influenced responses. This might be especially true for any students who were aware, formally or informally, about implicit theories and may have known what the socially correct responses are, namely high incremental and low entity. Given that high incremental and low entity is what was evident in the data, consistent with how response bias would influence implicit theories responses, future studies should consider reevaluating TOI and TOSA in relationship to classroom outcomes and while following a procedure that better encourages honest responses.

Under this logic, there is evidence of support for both TOSA variables, entity and incremental, as relevant domain specific predictors of final grade in an undergraduate statistics classroom. TOSA entity is already a significant negative predictor of final grade in the current results, and the strongest predictor in the study apart from covariates. If decreasing response bias were to show more true entity scores, this would strengthen TOSA entity results and result in a larger effect size. Decreasing response bias also may unmask true incremental scores, revealing whether or not a positive relationship does exist between TOSA incremental and final grade that is not present in the current results.

Results of implicit theories predicting transfer are similar to results for final grade, with TOSA entity emerging as a significant negative predictor of transfer in a regression model with both TOSA and TOI. TOSA incremental results, however, while not significant, are not only indicating lack of benefit for transfer but are indicating potential detriment. This is inconsistent with the theoretical implications of incremental theory and is not readily explainable. It might, however, be related to the problem of response bias previously discussed. If that is the case, eliminating bias may likely have the effect of future studies demonstrating null, rather than potentially negative, transfer predictions. Further complicating implicit theories results, however, is that incremental becomes a significant negative predictor and entity becomes non-significant when regressing transfer on TOSA alone.

Lack of results and presence of potentially problematic results does not necessarily mean lack of support for hypothesized relationships, however, especially given the amount of transfer observed in the sample. Given the small amount of transfer in evidence overall, lack of power might be playing a role in lack of demonstrated relationships. A known difficulty with measuring transfer is that it is not a widely demonstrated skill among students. One strategy that might help to increase power in future work would be to offer more transfer items and more items with statistical face validity. The two items in the current study that had the most successful transfer were items that included numbers (e.g., *SD* = .03) and obvious statistics language. Including more of these items should result in more students showing transfer evidence and as well as more differentiation between students. Increasing sample size would be another approach to increasing power for investigating transfer relationships.

Conclusion 3: Achievement goals do predict final grade and transfer. Moving to achievement goals as a predictor, results also demonstrated smaller and fewer relationships than anticipated. Notably, however, results show that mastery approach does predict final grade, supporting the notion that, of the four goals, mastery approach is the most likely to improve outcomes. Also, although mastery approach was the only significant predictor, results do not necessarily indicate lack of support for achievement goals or one of the achievement goals frameworks. Tentatively, regression results aside from significances show some support for the tri-partite framework of achievement goals (Elliot & Church, 1997) with mastery avoidance showing the smallest beta weight. It is unlikely that these results would indicate support for Dweck's (1986) performance/mastery conception of achievement goals, as the valence of approach or avoidance seems to be relevant in predictive power. Aside from the suggestion of domain-specific achievement goals, problems with the factorial conceptualization of achievement goals may also be contributing to lack of results. We return to potential factor problems in achievement goals after discussing their relationship with transfer.

When achievement goals were predicting transfer, regression results again demonstrated minimal support for hypothesized relationships. Despite fewer relationships than anticipated, however, performance avoidance emerged as a negative predictor of transfer. One thing this result might indicate is that, of the possible achievement goals, performance avoidance is the only goal that is detrimental for effectively using classroom knowledge beyond the classroom. In light of the positive predictive relationship between mastery approach and final grade, this seems to be further evidence that promoting mastery approach is a helpful goal. While mastery approach interventions may only directly improve final grade, they should also decrease the likelihood of students holding either performance goals or avoidance goals. Given that performance avoidance hinders transfer, promoting mastery approach should indirectly improve transfer by ameliorating performance avoidance goals.

Transfer results for achievement goals might also be related to factor issues in the achievement goals inventory. A number of achievement goals results indicate that additional factor analytic work should be conducted. As discussed, there have been many ways of classifying achievement goals and a definitive framework has yet to be universally accepted. From inter-correlations within the four factors, we saw evidence that the strongest relationships were between approach goals and between avoidance goals. In correlations with implicit theories, however, TOSA was related to mastery goals only, but not performance goals. Then, turning to predictions, mastery approach predicts final grade while performance avoidance negatively predicts transfer. Conducting competing confirmatory factor analysis (CFA) would allow for a comparison between the two-by-two achievement goals framework (Elliot & McGregor, 2001), the tri-partite framework of achievement goals (Elliot & Church, 1997), and theoretical conceptions of goals as approach versus avoidance only or performance versus mastery only. Comparing fit of the four CFA models would begin to give insight into which, if any, is a good fitting model of achievement goals. Exploratory factor analysis (EFA) could also be conducted on the twelve achievement goals items to explore whether or not an alternative factor structure might be suggested beyond those currently proposed for CFA. Results of these analyses might be especially helpful to distinguish what is driving the different predictive power of achievement goals for performance and transfer.

Conclusion 4: Path models offer minimal, inconclusive support of relationships. Overall, results for path-models were inconclusive. Given relative support for the re-specified Model A, however, there is tentative support for TOI over TOSA in a larger path model predicting performance. Support for Model A over Models B and C also gives tentative support for conceptualizing achievement goals on goal valence (approach/avoidance) rather than on both definition (mastery/performance) and valence simultaneously. Significant paths for both approach and mastery avoidance when predicting final grade also support an argument that goal valence is a more predictive conception of achievement goals than goal definition. Despite overall support for Model D, however, the negative predictive power of TOI incremental prevents an argument that Model D is supporting a TOI model of transfer over a TOSA model. Lack of predictive results for achievement goals also prevent the argument that goal valence is equally important when predicting transfer. Overall, lack of model fit among the models as well as lack of significant paths between implicit theories and achievement goals, could lead to an argument against implicit theories as an antecedent of achievement goals. Future studies might want to test whether or not models that present achievement goals and implicit theories as concurrent predictors (i.e. not predictive of one another) improve model fit or model predictions.

Tying into the question of factoring in the achievement goals framework, future studies could also consider structural equation modeling (SEM) to allow for a simultaneous investigation of the measurement as well as the structural components of achievement goals and implicit theories predicting either course performance or transfer. There is reason to believe that problems in measurement could be leading to problems in structure and evaluating whether or not the measurement component is sound would indicate whether or not the structure should even be considered. A similar avenue of investigation that would address the factoring of achievement goals would be to use exploratory structural equation modeling (ESEM), allowing all achievement goals items to load on all four achievement goals factors. Conducting ESEM in this way could compliment either EFA or CFA of achievement goals by demonstrating whether or not items are related to their factors in the same or different ways depending on whether or not they are being allowed to relate to other variables.

Implications for Classroom Interventions

Despite the need to revisit potential issues in future studies, there are a few classroom implications in the present results. First, there is reason to argue that remediating TOSA entity in a classroom intervention has the potential to improve both course performance and transfer outcomes. Conducting research on an implicit theories intervention in undergraduate statistics would also add to the argument that implicit theories are malleable and that moving them away from entity theory can improve academic outcomes. One intervention that could be considered is a contrasting-cases intervention. Contrasting cases would present students with examples of both entity and incremental students and would explain the detriments of entity mindset. This intervention could also explain the benefits of incremental mindset, despite lack of evidence in results that being an incremental theorist actually improves outcomes. Second, there is preliminary evidence to suggest that approach goals are helpful for outcomes while avoidance goals are harmful. Classroom activities and classroom talk that are actively designed to be approach oriented could be beneficial in promoting a classroom approach mentality. Writing-based interventions similar to those implemented by Bernacki et al. (2016) might also be considered as well as interventions similar to those suggested for implicit theories.

Despite the need for a good deal of future work, results of the current study overall indicate that achievement goals and implicit theories do play small but significant roles in student outcomes. Problems within the results also indicate that continued efforts to improve reliability and validity of the variables under investigation should result in stronger evidence of the relationship between goals, theories, and outcomes. Mixed results between regressions and path models indicate that the question of domain general or domain specific is still an open one, although preliminary results favor domain specificity.

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Appendix A

Transfer Items with Target Concepts and Score Breakdowns

1. We recently reviewed ratings for two new Psychology faculty members on RateMyProfessors.com. They both taught a Developmental Psychology course for the department last semester. Professor A had an overall rating of 4 (6 reviews, SD = 2.0); Professor B had an overall rating of 3.5 (57 reviews, SD = 0.3). If you had to take our Developmental Psychology in the future, based on the information provided, which professor would you choose and why would you choose him/her?
    a. Target concepts: Sample size/power; relationship between mean and standard deviation (Responses coded as showing evidence of transfer choose Professor B with greater power and smaller standard deviation)
    b. 14.5% of participants scored 2, 24.9% scored 1, 60.7% scored 0
2. A recent analysis in the *Commercial Appeal* ranked the psychology department at the University of Memphis as #6 in the state. The psychology department at Rhodes College was ranked #3 in the same list. The department chair at Rhodes commented in a recent interview that this ranking reflects that their students are twice as good as psychology students at the University of Memphis. Do you agree with his conclusion? Please provide a detailed explanation.
    a. Target concepts: Assumptions of ordinal vs. ratio data; biased raters; and variables composing the analysis (i.e. only rankings based on student variables can lead to conclusions about students.) **Of note: Mention of ordinal vs. ratio was required for a score of 2.
    b. 11% of participants scored 2, 22.1% scored 1, 66.9% scored 0

3. Our prior research shows that students who take the research methods and statistics sequence through the Psychology department tend to perform better in the first year of graduate school. According to a quote in the *Daily Helmsman* from a newly hired dean of graduate studies, “If methods and statistics courses cause better performance during the first year of graduate school, then these courses should be a requirement for every student who intends to go to graduate school.” Do you agree with the Dean? Should this course be mandatory? Why or why not.
    a. Target concepts: Correlation is not equal to causation; problem of third variables.
    b. 4.6% of participants scored 2, 4% scored 1, 91.4% scored 0.
4. Questionnaires administered to psychology majors have demonstrated that students enrolled in online courses tend to have better final grades than those enrolled in comparable in-person courses. The psychology department is contemplating making undergraduates take more online courses because they result in students getting better grades. Do you agree with the psychology department? Should online courses be mandatory? Why or why not.
    a. Target concepts: Correlation is not equal to causation; problem of third variables; problems with non-random/quasi-experimental/self-selecting samples.
    b. .6% of participants scored 2, 13.2% scored 1, 86.2% scored 0