AN EXPECTANCY VALUE THEORY PREDICTS ACHIEVEMENT IN UNDERGRADUATE STATISTICS THROUGH ACADEMIC DELAY OF GRATIFICATION

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ABSTRACT

We tested a model that integrates academic delay of gratification with Expectancy Value Theory to predict achievement in an undergraduate psychology and nursing statistics class at a metropolitan university in the southeastern United States. We analyzed measurements (n = 163: 80.4% female) of past performance, academic delay of gratification, effort, value, affect, and cognitive competence with students' final exam score. The path model analyzed explained 14.9% of the variance in scores. Past performance in mathematics and student effort had direct effects on grades and all expectancy value theory constructs, as well as academic delay of gratification, were indirectly related to grades. We present details of our analysis and discuss theoretical and pedagogical implications of this study.

Keywords: *Statistics education research; Statistics achievement; Effort; Persistence; Path analysis; Self-regulation*

1. INTRODUCTION

Due to its many educational, professional, and personal benefits, statistics is widely considered one of the most important subjects in the university curriculum (Brown & Kass, 2009; Jordan & Haines, 2006). Statistical reasoning is a vitally important skill that prepares college graduates to be competent consumers of research in their daily lives, and it is one of the most sought-after skills in graduate school (Aiken et al., 1990; Stefan et al., 2015). Students who continue their statistics training are well-positioned to gain entry into a wide range of fast-growing and lucrative careers, including statistics, research, data science and analytics (Bureau of Labor Statistics, 2018; Manyika et al., 2011; Rees et al., 2006). Given the crucial role that statistics plays in our increasingly data-driven society, it is unfortunate that it is an especially challenging topic to teach and learn (Ben-Zvi & Garfield, 2004; Gordon, 2004; Horton & Hardin, 2015) and many students approach a class in statistics with fear, dislike, disinterest, and/or low confidence in their ability to learn the topic (Dempster & McCorry 2009; Garfield, 1995; Garfield & Ben-Zvi, 2007; Schau et al., 2012; Tremblay et al., 2000). The difficulties involved in teaching statistics are usually confounded by having a wide range of student abilities and motivations in the typical undergraduate classroom (Garfield & Ben-Zvi, 2007; Macher et al., 2013; Tremblay et al., 2000), and by past experiences with mathematics that result in unfavorable attitudes toward statistics and negative self-concepts (Marsh & Yeung, 1997; Onwuegbuzie & Wilson, 2003).

Statistics education is a growing field but is fragmented and difficult to integrate, due to the fact that studies are spread across many disciplines that cover a variety of methodologies and perspectives (Zieffler et al., 2008). The piecemeal nature of the literature leaves educators with little guidance on factors that promote student achievement. Several studies, using different measures of statistics attitudes, have found that students' attitudes toward statistics predict statistics achievement (Chiesi & Primi, 2010; Nasser, 2004; Roberts & Reese, 1987; Schau et al., 1995; Wise, 1985) and other studies

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have demonstrated the importance of student characteristics, such as math background (Dupuis et al., 2012; Nasser, 2004; Onwuegbuzie & Wilson, 2003; Sorge & Schau, 2002). Compared to other fields of study, however, statistics education has only recently begun to build a separate body of theory (Gal & Ginsburg, 1994; Ramirez et al., 2012).

1.1. EXPECTANCY VALUE THEORY

Although it was originally designed to explain achievement motivation of children and adolescents, especially with regard to mathematics, one of the most prominent theoretical perspectives on achievement motivation in school has been Expectancy Value Theory (EVT; Eccles, 1983; Wigfield & Eccles, 2000). As pointed out by Ramirez and colleagues (2012), the motivational constructs in EVT parallel closely measures in the Survey of Attitudes Toward Statistics (SATS-28, SATS-36; Schau, 1992, 2003), which consists of six separate subscales pertaining to statistics: *Affect*, *Cognitive Competence*, *Effort*, *Value*, *Interest*, and *Difficulty*. As applied to student achievement, the basic thesis of achievement motivation theories is that students' choice, effort, persistence, and achievement can be explained by their motivations, such as liking the subject (*Affect*), how well they believe they will perform in a course (*Cognitive Competence*), the extent to which they value the subject (*Value*), and how difficult (*Difficulty*) they believe the course material is to learn (Wigfield, 1994; Wigfield & Eccles, 2000). Two studies were found that used Eccles' EVT to predict achievement in undergraduate college level statistics courses (Hood et al., 2012; Sorge & Schau, 2002). Both studies were similar in that they derived a final model, based on results from a more complicated model, shared a core set of EVT constructs, and tested many of the same theoretical pathways that are depicted in EVT. In their study of 177 engineering students, Sorge and Schau (2002) used results from their original structural equation model to derive a final model in which affect and previous achievement were the only constructs that had a direct effect on achievement. In agreement with other studies (e.g., Hood et al., 2012; Wise, 1985; Wisenbaker et al. 1999; Wisenbaker et al. 2000), the results did not support the EVT prediction that students' perceptions of the value of statistics would have a direct influence on achievement. There was a direct influence between affect and achievement (see also Budé et al., 2007), but other studies have failed to support the relationship (see Scott, 2001, for a review). Notably, Hood and colleagues (2012) conducted a similar EVT analysis involving 149 second-year psychology students in Australia that, in agreement with Sorge and Schau (2002), found the relationship between value and achievement lacking.

Both studies also reported direct effects between past performance and achievement, as well as several indirect effects that are difficult to compare, due to differences in the models that were tested. For example, unlike the Australian study, Hood and colleagues (2012) added expectancies of success, as a mediator between all EVT constructs and achievement, and they included effort in their model, which resulted in important differences in the indirect effects that were tested in the studies. Despite the differences between the two studies, both studies came to the same conclusions regarding the direct effects of EVT constructs and achievement. Neither study found a direct effect between value and achievement, and both studies found a direct effect between previous performance and achievement. Only Hood and associates included effort and expectancies in their model and both constructs had direct influences on achievement.

1.2. SELF-REGULATORY BEHAVIOR

Like Hood and colleagues (2009), Sorge and Schau (2002) failed to find a positive relationship between value and statistics achievement. In other words, cognitive confidence was related to affect and affect was related to value but there was not a direct or indirect relationship between value and achievement. An explanation for these findings would be useful to the statistics education field because the value–achievement link is one of the most important predictions of EVT. Considering the causal chain of events in EVT, cognitive competence, affect, and difficulty should influence value and expectancies of success, and value and expectancies should directly influence achievement (Wigfield & Eccles, 2000). Hood and colleagues made an important contribution by adding expectancies of future success as a mediator between value and achievement. They also tested paths from cognitive competence (i.e., current beliefs) to expectancies of future success and from expectancies to achievement. In our study, we sought to find a different mediating effect of the value to achievement relationship, one that goes through academic delay of gratification (ADOG) and student effort. It should be noted that, one of the conclusions of Hood and colleagues study was that future research is needed to investigate the cost-benefit decision making that students undergo with regard to expending effort on the course, rather than devoting their time to other competing activities.

EVT predicts that students who are confident, have positive affect, and value statistics are likely to be motivated, exert effort, persist, and succeed. Studies based on EVT, however, have not accounted for self-regulatory behaviors that successful learners often possess (Pintrich, 2004; Zimmerman & Pons, 1986). Conceptual frameworks on student motivation and learning among college students assume that self-regulatory behaviors mediate the relationships between the student, context, motivation, and eventual learning (Pintrich, 2004). Being motivated is often not enough to ensure that students will engage in behaviors that are necessary to succeed (Locke & Latham, 1990), especially when there are multiple alternatives competing for students' attention (e.g., work, family, recreation). Self-regulated learners develop a plan of action, set priorities, and are less likely to procrastinate (Wolters, 2003). A common theme in the self-regulated learning (SRL) literature, setting it apart from many other traditions, is its emphasis on students' role in their education (Zimmerman & Schunk, 2001). Students are viewed as self-regulated learners when they are proactive, take the initiative, monitor their own activities, and make plans to achieve educational goals.

1.3. ACADEMIC DELAY OF GRATIFICATION

Delay of gratification, first studied by Mischel (1981), is the ability to, when given a choice between an immediate but relatively minor reward and a temporally distant but relatively major reward, preclude oneself from the immediate gratification in order to attain the more satisfying gratification later. Academic delay of gratification (ADOG) is the same concept applied to the academic sphere, as it is a common occurrence that a student would have to choose between a number of competing activities and academic activities such as studying. Bembenutty (2008) conceived of ADOG as a motivationally-determined choice between immediate and delayed rewards and connected EVT and ADOG, finding a positive correlation between liking (affect), importance (value), and expectancy (cognitive competence regarding a goal) and ADOG, operationally defined by the Academic Delay of Gratification Scale (ADOGS) (Bembenutty & Karabenick, 1998). Based on extensive relations between self-regulation and ADOG (Bembenutty & Karabenick, 2004), Bembenutty (2009) also proposed that ADOG is a self-regulatory activity which monitors and controls behavioral aspects of academic achievement. We note once more, as Mischel and Ayduk (2002) state, "But even when motivation is high, self-control in the face of temptations and frustrations requires more than good intentions" (p. 114).

1.4. THE CURRENT STUDY

The current study builds on the two studies reviewed above, as well as a model developed by Ramirez and colleagues (2012), called the Students' Attitudes Toward Statistics Model (SAT-M). Based on Eccles' EVT, SAT-M posits causal paths in which student characteristics predict previous achievement-related experiences, student characteristics and previous achievement-related experiences predict statistics attitudes (i.e., affect, cognitive competence, value, difficulty, and interest), statistics attitudes influence effort, and all of these factors predict achievement in the statistics course. Ramirez and colleagues reviewed 17 studies that assessed attitudes toward statistics (Schau, 1992, 2003) to predict statistics achievement and found support for the affect, cognitive competence, and value subscales but not for the difficulty subscale (i.e. students' attitudes about the difficulty of statistics as a topic). Our aim is to test an integrated EVT-M model, with the addition of ADOG and effort, as a mediating pathway between value and achievement. Hood and colleagues (2012) reversed the role of affect and competence but kept value as the next variable in their model and added expectancies of success as a mediator between values and achievement. Effort, however, was not part of the sequence of influences on achievement, as would be expected in EVT.

Considering the important role student effort plays in EVT and SAT-M, and evidence that effort has a direct effect on achievement (Hood et al., 2012; Lalonde & Gardner, 1993; Wang & Newlin, 2000), we used an objective measure of student effort (the number of times students view content in the online course) as a possible improvement to the two EVT guided studies reviewed above. Sorge and

Schau (2002) did not include effort in their model, and Hood and colleagues (2012) used the number of tutorial sessions attended as their measure of effort (maximum of 11 sessions). Guided by Ramirez and colleagues' review, we did not include the EVT construct that measures students' attitudes about the difficulty of statistics in our model but, given the paucity of comparable studies to guide our initial model, direct paths were included between all of our EVT motivational attitudes (i.e., cognitive competence, affect, and value) and student achievement (see Figure 2), as EVT would predict.

Study hypotheses The first hypothesis is that there will not be direct influences for cognitive competence or value. As previously discussed, we hypothesize that the value → ADOG → effort → achievement pathway will mediate the direct relation between value and achievement.

2. METHODS

2.1. PARTICIPANTS

Participants in the study were undergraduate nursing and psychology students in a web-based introductory statistics course at a metropolitan university in the southeastern United States (n = 163). Less than ten percent of the sample was psychology students and preliminary analysis found no support for including discipline as a covariate. We combined data from seven classes of the same Blackboard course, over a 2½ year period. Demographics of the participants were as follows: 131 (80.4%) females, 30 males (18.4%) and two declined to answer; 119 (73.0%) self-specified as White, 29 (17.8%) as Black or African American, 5 (3.1%) as Hispanic or Latino, 3 (1.8%) as Asian or Pacific Islander, 1 as Native American or American Indian, and 1 as Other, with 5 (3.1%) not specifying an ethnicity; and 25% between the ages of 18 and 24, 41% between the ages of 25 and 34, 25% between the ages of 35 and 44, and the remaining 9% were older than 44.

2.2. PROCEDURES AND MEASURES

Prior to collecting data, the study was approved by the University Human Subjects Review Board. Students participating in the study were asked, at the beginning of the course, to answer five-point Likert questions pertaining to their attitudes toward mathematics and statistics, in addition to demographic questions. All participants were given five extra points for participating in the study; participation in the study, however, was strictly voluntary and not required. Out of 189 total students, 26 were eliminated from the study because 6 refused to provide consent to participate, 6 were taking the course for the second time, 5 withdrew from the course, and 9 failed to take the final exam. The course was designed by the instructor, with the aid of an instructional designer, and it received Quality Matters certification (*Standards from the Quality Matters Higher Education Rubric,* 6th Edition). The course was designed so students would have access to every lecture that students in the face-to-face classes receive, via lecture videos created by the instructor. Students were told that over 90% of test questions would be taken directly from the lecture videos with the remaining questions coming from other documents on Blackboard. The textbook was considered supplemental material and a significant proportion of the students did not purchase the textbook. With Blackboard keeping track of student activity, this course design gave the instructor a good estimate of overall effort in the class. In order to keep the classes as similar as possible, all classes were taught by the same instructor and no changes were made to the course during the study. Course content and instructions remained constant, and the instructor made a concentrated effort to maintain a consistent approach to class management, rapport, and communications style.

Achievement Student scores on the final exam (worth 65 points) were used as a measure of statistics achievement. Throughout each section of the course, students took the same tests except that numbers were changed and questions were rephrased so that all tests assessed the same learning objectives, at the same level of difficulty, and in the same question formats. The exams were timed, consisted of multiple choice, short response questions, and calculation problems. The test assessed material typically covered in required undergraduate statistics courses in psychology and nursing programs. For example, tests covered the language of statistics (e.g., definitions), logic of statistics (e.g., null hypothesis testing, type I error, type II error, power), and hand calculations (e.g., probability, chi-square, odds ratios, risk ratios, variance, standard deviation, *t*-tests, *z*-tests, ANOVA tables, etc.).

Math and Statistics Attitudes A concern about statistics attitudes measures is that we cannot be sure how students form attitudes about statistics when they have never taken a course in statistics, bringing the validity of the measures into question when assessed at the beginning of a course. All students enrolled in undergraduate statistics courses, however, have taken multiple math courses and students' attitudes toward statistics are likely heavily influenced by previous experiences in math courses (Gal & Ginsburg, 1994; Perney & Ravid, 1990; Roberts & Reese, 1987). Because attitudes were assessed at the beginning of the semester, most of our measures of attitudes pertained to math classes. Six items in a questionnaire were developed for use in this study, partially based on several previously validated measures concerning attitudes towards math and statistics by Brookstein et al. (2011), Ramirez et al. (2012), and sample measures of EVT constructs (Wigfield & Eccles, 2000). For each item, participants responded using a five-point Likert type scale, with possible responses ranging from, "Strongly Disagree" (coded as 1) to "Strongly Agree (coded as 5)." The items were also viewed in the larger framework of the SAT (Schau et al., 1995), using the following measures: *Value* was the sum of two items ("I think mathematics is important in life" and "I think statistics is important in life"), *Affect* was the sum of two items ("In the past, I have enjoyed math classes" and "In middle and high school, I enjoyed math classes"), and *Cognitive Competence* consisted of one item ("In middle school and high school, I felt confident in my ability to solve math problems"). *Past Performance* was one question ("In middle school and high school, I received good grades in math classes (i.e. usually above a C.)").

Academic Delay of Gratification Ten items from the Academic Delay of Gratification Scale (Bembenutty & Karabenick, 1998) measure Academic Delay of Gratification. Each item contained a scenario with two courses of action. One sample scenario asked respondents "Suppose that you had a choice between ... A. Study a little every day for an exam in this course and spend less time with your friends, OR B. Spend more time with your friends and cram just before the test." Respondents chose between "Definitely Choose A," "Probably Choose A," "Probably Choose B," and "Definitely Choose B." A second scenario was "Suppose you had a choice between … A. Leaving the library to have fun with your friends and try to complete an assignment that is due the next day when you get home later that night, OR B. Staying in the library to make certain that you finish the assignment." The responses were coded '1' through '4' so that higher scores represented choosing to delay gratification in an effort to make a better grade (this particular question was reverse coded).

Effort Student online activity, or the number of times a student accessed the course content, was recorded by the Blackboard learning management system. Over 90% of course instruction was 3 to 8-minute videos produced by the course instructor, and the guidance provided for all five units of the class explained that the course videos were, by far, the most important part of the course. The measure of effort used in this study is considered a more accurate measure of student study behavior than student self-report measures that are especially susceptible to bias (Schwartz, 1999) as well as other attempts that have been made to improve measurement, such as ratings of effort by statistics tutors (e.g., Budé et al., 2007). The measure is similar to the one used by Wang and Newlin (2000), whose measure, *online activity*, had a component which recorded the number of times a student accessed the course homepage.

2.3. ANALYTIC PLAN

SPSS 25.0 (IBM Corp., 2017) was used to merge data, create measures from item-level data sets, and check for multicollinearity and outlier issues. Path analysis was performed with lavaan (Rosseel, 2012), a package available in R. Adequacy of model fit was assessed with an absolute fit index, Standardized Root Mean Square Residual (SRMSR), a parsimony index, Root Mean Square Error of Approximation (RMSEA) (Steiger, 1990), and two incremental fit indexes, Comparative Fit Index (CFI) and the Non-Normed Fit Index (NNFI). The SRMSR is calculated as the standardized difference between the observed and predicted correlations and ranges from 0 to 1. A value of zero represents a perfect fit and values less than 0.08 are generally regarded as evidence of a good fit (Hu & Bentler, 1999). The SRMSR does not penalize the model for complexity (i.e., more paths in the model) but the RMSEA adjusts fit based on the Chi-Square to degrees of freedom ratio. Values of less than 0.06 and 0.08 are considered good and adequate fit respectively and values over 0.10 are consider a poor fit (MacCallum et al., 1996; Hu & Bentler, 1999). The CFI compares the hypothesized model with the model with no correlations (the independence model) and penalizes for every parameter that is estimated. The NNFI also compares the model of interest with the null model and it is preferable for smaller sample sizes. CFI and NNFI values above 0.95 are considered good fit (Hu & Bentler, 1999).

On the basis of recommendations by MacKinnon and colleagues (2002), we used bootstrapping techniques in order to obtain estimates of standard errors and 95% confidence intervals for all indirect effects. Bias-corrected confidence intervals were derived from 100,000 bootstrap samples. This method of testing indirect effects is particularly useful in relatively small samples and when there are multiple simultaneous mediators (Preacher & Hayes, 2008). All subjects had scores on the final exam and effort (n = 163). The remaining variables had missing values: Affect = 8, Cognitive competence = 6, value and ADOG = 4. Full information maximum likelihood (FIML) was utilized to address missing values.

3. RESULTS

3.1. DESCRIPTIVE STATISTICS AND CORRELATIONS

Descriptive statistics and correlations for all study variables are shown in Table 1 and a scatter matrix and histograms are in Figure 1. Responses to all attitudinal questions were higher than the midpoint (i.e., 3.0) of the Strongly Disagree to Strongly Agree (coded 1 to 5) response choices. Past performance and cognitive competence had an observed range from 1 to 5 (skewness = -1.21 and -0.52 respectively), and affect and value had an observed range from 2 to 10 (skewness = -0.24 and -0.97 respectively).

Table 1. Descriptive statistics and correlations between predictors and final test scores

Variable	Mean	SD	1	2	3	4	5	6
1. Past Perf.	3.98	1.13	--					
2. Cog. Comp.	3.44	1.30	.69(.00)	--				
3. Affect	6.36	2.59	.63(.00)	.83(.00)	--			
4. Value	8.09	1.36	.33(.00)	.24(.00)	.31(.00)	--		
5. ADOG	3.36	0.41	.17(.03)	.11(.17)	.12(.13)	.29(.00)	--	
6. Effort	173.47	92.08	-.05(.53)	-.02(.80)	-.08(.31)	.01(.90)	.19(.02)	--
7. Final test grade	41.84	15.59	.24(.00)	.21(.01)	.19(.02)	.12(.13)	.11(.17)	.27(.00)

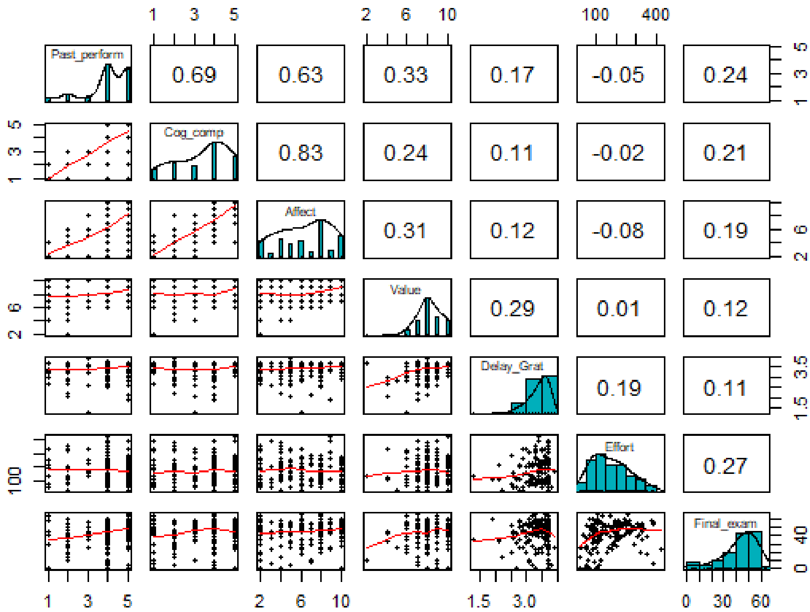
p-values in parentheses

Effort had the strongest bivariate relationship with grades ($r(161) = 0.27$, $p < 0.001$) and past performance had the second strongest association with grades ($r(157) = 0.24$, $p = 0.002$). Cognitive competence ($r(155) = 0.21$, $p = 0.008$) and affect ($r(153) = 0.19$, $p = 0.016$) were also related to grades. Past performance was strongly related to cognitive competence ($r(155) = 0.69$, $p < 0.001$) and affect ($r(153) = 0.63$, $p < 0.001$) and moderately related to values ($r(157) = 0.33$, $p < 0.001$) and ADOG ($r(157)$, = 0.17, $p = 0.030$). The strongest relationship in the matrix was between cognitive competence and affect ($r(153) = 0.83$, $p < 0.001$). Affect was moderately related to value ($r(153) = 0.27$, $p = 0.001$), value was moderately related to ADOG ($r(157) = 0.295$, $p < 0.001$), and ADOG was related to effort ($r(157) = 0.189$, $p = 0.017$).

3.2. PATH ANALYSIS

Prior to testing the path model, a regression analysis was conducted to test for collinearity and outlier problems. The highest variance inflation factor was 3.92 and the highest Cook's distance was 0.25, indicating that collinearity and influential data points were not a problem.

Figure 1. Scatterplot matrix, histograms, and correlations



The initial model fit was good, $\chi^2(10) = 10.45$; $p = 0.402$, RMSEA = 0.017, CFI = 0.999, and NNFI = 0.997. The model explained 15.6% of the variance in final test scores. Effort was the only variable showing a direct effect on grades ($\beta = 0.286$, $p = 0.001$), which supports the first hypothesis that cognitive competence and value will not have direct influences on achievement.

Modification indices suggested deleting three direct paths to achievement: those from cognitive competence, value, and affect. We kept the path from value to achievement in the revised model, however, as part of a test of the hypothesis that the value → ADOG → effort → achievement pathway will mediate the direct effect of value on achievement. The fit of the revised model was good, $\chi^2(12) = 11.220$; $p = 0.510$, RMSEA = 0.000, SRMR = 0.037, CFI = 1.00, and NNFI = 1.004. With only three variables with a direct effect on final test scores, the model explained 14.9% of the variance in the final test scores. Unstandardized (B) direct and indirect effects, as well as 95% confidence intervals, can be found in Table 2. For direct effects, standardized path coefficients (β) are reported in the text and displayed in Figures 2 and 3. Indirect effects are reported in the text, and Table 2, with unstandardized bias corrected bootstrap confidence intervals. Past performance was related to cognitive competence

Table 2. Direct and indirect effects in the revised model

Predicted	Predictor	Unstandardized estimate	*p*-value	95% Confidence interval
Direct effects				
Competence	Past performance	0.803	< 0.001	(0.697, 0.901)
Affect	Past performance	0.217	0.060	(-0.009, 0.446)
	Competence	1.518	< 0.001	(1.314, 1.705)
Effort	ADOG	42.039	< 0.001	(12.986, 73.385)
Value	Affect	0.168	< 0.001	(0.084, 0.261)
ADOG	Value	0.090	0.002	(0.035, 0.151)
Grade	Value	0.411	0.669	(-1.564, 2.201)
	Effort	0.048	< 0.001	(0.018, 0.077)
	Past performance	3.420	< 0.001	(0.870, 6.027)
Indirect effects				
Grade	Past performance	0.044		(0.010, 0.130)
	Competence	0.046		(0.011, 0.140)
	Affect	0.031		(0.007, 0.090)
	Value	0.182		(0.042, 0.485)
	ADOG	2.025		(0.579, 4.422)

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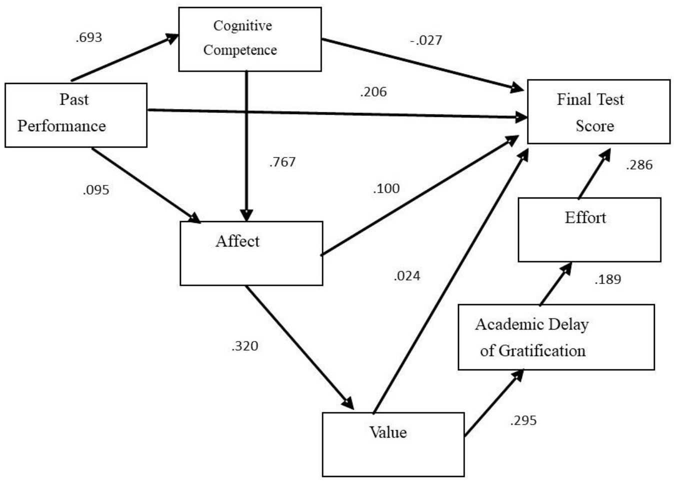

Figure 2. Initial model: Standardized estimates for Expectancy Value Theory of Motivation and Academic Delay of Gratification predicting undergraduate statistics grades

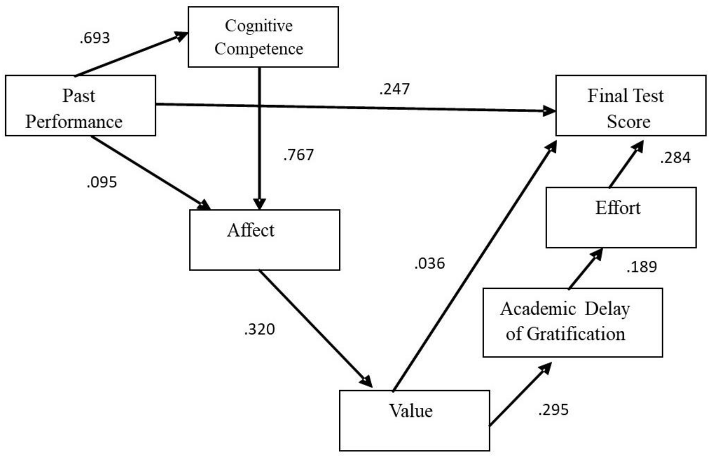

Figure 3. Revised model: Standardized estimates for Expectancy Value Theory of Motivation and Academic Delay of Gratification predicting undergraduate statistics grades

($\beta = 0.693$, $p < 0.001$) and it was directly and indirectly related to course grades ($\beta = 0.247$, $p = 0.009$, and B = 0.046, 95% CI: (0.011, 0.140) respectively). There appears to be hypothesized paths between the EVT constructs: cognitive competence to affect ($\beta = 0.767$, $p < 0.001$) and affect to value ($\beta = 0.320$, $p < 0.001$).

The second hypothesis was supported. Value did not have a direct effect on final test scores ($\beta = 0.036$, $p = 0.669$), but there appears to be an indirect effect from value to achievement (B = 0.182, 95% CI: (0.042, 0.485)). Value predicted ADOG ($\beta = 0.295$, $p = 0.002$), ADOG was related to effort ($\beta = 0.189$, $p = 0.006$) and there appears to be a path from effort to final test scores ($\beta = 0.284$, $p = 0.001$). Past performance, cognitive competence, affect, value, and ADOG showed indirect effects on achievement, but the effects were especially small for past performance (B = 0.044), competence (B = 0.046), and affect (B = 0.031).

4. DISCUSSION

Given the importance of statistics education, there have been surprisingly few empirical investigations into the determinants of achievement in undergraduate statistics classes and even fewer studies have contributed to a separate body of theory. EVT posits that positive attitudes are motivational factors that should result in student engagement as well as achievement. Studies that have used EVT to predict grades in undergraduate statistics, however, have provided relatively weak and inconsistent evidence to support this claim. The current study expanded on the research of Sorge and Schau (2002) and Hood and colleagues (2012). Following the lead of these two studies, an integrated EVT model was tested, with direct paths from EVT constructs to final exam scores. Overall, results from the initial model support findings from the two previous studies, as well as earlier studies, regarding direct paths from EVT constructs and course grades. These results, as well as the findings reported by Hood and colleagues, further support the conclusion of Sorge and Schau that the value → achievement relationship needs further investigation. The current study suggests that valuing statistics does not have a direct effect on achievement, and future studies should investigate constructs related to motivational and self-regulatory factors as mediators of the relationship.

A myriad of educational research has shown that EVT adequately explains how student attitudes are linked to academic achievement (Wigfield & Eccles, 2000), but past research has failed to account for key EVT relationships when achievement in undergraduate statistics is the outcome. Unlike the current study, Hood and colleagues (2012) did not find a relationship between affect and value. They did, however, find an indirect relationship between value and statistics achievement, through expectancies of success. This study tested a different pathway from value to student achievement, a pathway that follows up on the cognitive competence → affect → value sequence of relationships found in the Sorge and Schau (2002) study (Hood and colleagues reversed the path (arrow) between cognitive competence and affect). In order to address their call for further investigations into the value–achievement relationship, we looked into factors that would explain how motivated students would exert the effort that is usually required in order to learn statistics. Based on a self-regulatory perspective on student learning in college (Pintrich, 2004) and Bembenutty's (2008) research on ADOG, we added ADOG between students' perceived value of statistics and the effort that they devote to the course. In order to complete the connection to achievement, student effort was hypothesized to predict final exam scores (achievement).

A revised model, excluding two paths in the initial model, was tested and fit the data well. Results from the initial model and the revised model, support the inclusion of ADOG and student effort as a mediating pathway between students' perceived value of statistics and final exam scores. EVT posits that motivated students will persist and succeed but ADOG compliments the theory by specifying a self-regulatory mechanism through which motivated students monitor and persist in their efforts to succeed. Bembenutty (2008) proposed that ADOG is a motivationally-determined choice between immediate and delayed rewards, which places motivation prior to ADOG in a causal sequence. He also proposed that ADOG is a self-regulatory activity, which monitors and controls behavioral aspects of student learning (Bembenutty, 2009), fitting well with ADOG's role as a mechanism that explains how motivated students persist in their efforts to succeed. This is the first attempt to integrate a self-regulatory mechanism with EVT, to predict achievement in an undergraduate statistics class. Clearly, future studies are needed that further explore the role self-regulation plays in this area of research.

As expected, and in agreement with previous studies (Harlow et al., 2002; Hood et al. 2012; LaLonde & Gardner, 1993; Sorge & Schau, 2002), previous performance in math courses was directly related to final exam scores. The results support the interpretation that students' previous math ability increases their cognitive competence, which results in positive feelings about statistics (i.e. affect), positive affect increases student perceptions of the importance of statistics (i.e. value), value increases ADOG, ADOG increases student effort, and effort has a positive influence on student achievement.

There are some important limitations to this study. The sample was derived from psychology and nursing students from a fully online statistics course at a metropolitan university in the southeastern United States. The design of statistics courses is heavily influenced by the academic discipline as well as factors such as institutional, cultural, and student characteristics (Brown & Kass, 2009; Roiter & Petocz, 1996). As a result, the assessment of student learning can vary widely, resulting in differences in the way achievement is measured. There are other measurement issues worth noting. The EVT measures in the present study were only one or two questions but the measures in the other two studies were six, seven, or nine item scales from the Survey of Attitudes Toward Statistics (Schau, 1992) or the Survey of Attitudes Toward Statistics (Sorge & Schau, 2002) designed for engineering students. Relatedly, our study primarily asked about attitudes toward mathematics whereas the other studies asked about attitudes toward statistics. We reasoned that our students never had a course in statistics and may have had inaccurate perceptions of statistics going into the class. All students had multiple mathematics classes prior to taking statistics, and we know that students usually make strong associations between mathematics and statistics. Regardless, differences in measures likely account for differences in the results across studies. Our model only explained 14.9% of the variance in exam scores, the Sorge and Schau (2002) model explained 76%, and the Hood et al. (2012) study explained 40%. Some of the higher explained variance in the Sorge and Schau study is likely a function of their use of latent variables, which serves to reduce measurement error and increase effect sizes (Bolen, 1989). The relative strength of past performance, as a predictor of statistics achievement, is one of the most important findings that researchers and instructors should keep in mind. Past performance explained more than half of the total explained variance in the current study and the Hood et al. study (i.e. 7.5% and 22% respectively), and approximately two-thirds of the total explained variance in the Sorge and Schau (2002) study. This reminds us that student achievement is heavily influenced by past experiences in same or similar domains, suggesting that our understanding of achievement must be viewed from a developmental perspective.

Another important issue is that differences in the models tested can have a significant influence on comparisons of results across studies. As pointed out earlier, there are several differences in constructs that are included in different studies as well as choices in the pathways that are specified. Even including reciprocal effects in a model can significantly complicate comparisons between that model and an identical model that does not include them. It is noteworthy, however, that, despite different samples, models, and measures, similar relationships were found in all three studies. In addition, results from this study shared many important theoretical findings across studies from different disciplines and cultures. For example, a dissertation by Naccache (2012) found many of the same relationships in a sample of business students in Lebanon. Moreover, from theoretical and pedagogical viewpoints, the current study suggests that researchers and instructors alike can benefit from looking into possible mediators of the attitudes → effort pathway to achievement in undergraduate statistics classes.

When students enter a classroom, they already have a long history of experiences in the math domain and the skills that they bring to the class have a substantial influence on their achievement, as many studies have demonstrated—including the current study. By the time students enroll in a mandatory undergraduate statistics class, there are likely powerful attitudinal and self-evaluative forces that have them on a trajectory that is difficult to change. The significant chain of relationships, from cognitive competence to effort and achievement found in this study, supports predictions by EVT and research on self-efficacy beliefs. Decades of research on Bandura's social cognitive theory supports the proposition that students with high self-efficacy beliefs (i.e., belief in their ability to obtain a desired goal) tend to view difficult tasks (such as statistics) as a challenge rather than something to avoid, and they are more likely to persist in the face of obstacles (Pajares, 1997). Undergirding social cognitive theory is the self-system, which serves as a self-regulatory mechanism in which individuals continuously monitor and evaluate interactions between themselves and their environments, which allows them to influence their own thoughts and actions. Social cognitive theory provides some useful suggestions that complement the implications of research by Dweck and colleagues (2006). Social cognitive theory supports raising self-efficacy beliefs, through genuine and meaningful mastery experiences. Through best teaching practices, as well as a significant amount of student effort, students can acquire authentic mastery of the topic, which will hold up during the iterative process that students go through when the self-system continuously monitors and re-evaluates progress in the domain of statistics learning.

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