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Exploring Achievement Behaviors in Non-Major Statistics Course: An Expectancy-Value Perspective and Thoughts for Practice

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Abstract: Statistics education is increasingly important to our society with enrolment increases of 16% in introductory statistics courses and 85% in upper-level statistics courses. Research has demonstrated many factors related to students' behaviors and outcomes in statistics courses such as past achievement, attitudes, and effort. We sought to model these factors together to better understand how introductory statistics students' attitudes were related to students' achievement behaviors and what student characteristics mediated such relationships. Structural equation modeling with data from N=301 students in an introductory statistics course for psychology majors revealed that majors with higher GPAs had more interest, enjoyment as well as utility value for statistics, and these variables were in turn related to expectations for success or achievement behaviors. Females had lower interest in statistics, and this was related to lower expectations of success. The findings highlight the need to increase interest and enjoyment and utility value for non-majors studying statistics. Recommendations for how to adapt the statistics classroom to that end are discussed.

Keywords: statistics education, expectancy-value theory, achievement behaviors, college students

Introduction

Attitudes towards statistics have been demonstrated to have an important relationship to students' achievement behaviors in a statistics course and course outcomes (Emmioğlu & Capa-Aydin, 2012; Nguyen et al., 2016). In the field of statistics education, "attitudes" refer to constructs such as perceived cognitive competence with statistics, interest in statistics, affect when learning statistics, value of statistics and perceived difficulty in learning statistics. Reviews of the research on statistics attitudes show that attitudes correlate with achievement behaviors and higher statistics course outcomes (Emmioğlu & Capa-Aydin, 2012; Ramirez et al., 2012). Studies have demonstrated that negative attitudes towards statistics, such as lower levels of interest or value, are related to lower course grades (Cashin & Elmore, 2005) and lower test and quiz scores (Tempelaar et al., 2007).

There is a strong social need for students to learn statistics. The National Science Foundation (NSF; 2018) highlights the need for developing a "21st century data-capable workforce." The ability to run statistical analysis and the ability to interpret, communicate, and use statistics are critical skills for building such a workforce. Most current estimates suggest that more than 500,000 students take an introductory statistics course at the college level per semester and this number is growing rapidly (American Statistical Association, 2012). However, many students have difficulty when taking such courses (Murtonen & Lehtinen, 2003) and further research demonstrates that many of these students have negative attitudes towards the subject and this will inhibit their ability to learn the statistics thereby reducing the ability to achieve the levels of literacy needed in our society. This makes attention to statistics attitudes and the factors that play a role in students' attitudes imperative if we are to address, and, hopefully, improve students' attitudes (Shau, 2003).

While instructors may be aware of students' negative attitudes towards statistics, and a great deal of literature exists on strategies for improving students' attitudes towards statistics, there is little published on the frameworks that inform how these attitudes manifest and function. Rather, studies commonly focus on what attitudes students hold at a particular point in time, or perhaps before and after an intervention. What is missing, however, is a broader understanding of how various factors not only directly but indirectly influence students' attitudes towards statistics to begin with. By understanding the more nuanced details we can develop classroom activities that better fit the needs of our students. Without this understanding, efforts to improve attitudes may be futile. Therefore, the purpose of this study is to examine a model of how attitudes play a role in students' attitudes toward learning statistics, how the attitudes interact with other student characteristics, and ultimately how attitudes manifest in students' learning behaviors. We used the expectancy-value model (Eccles et al., 1983) as a guiding framework for understanding students' attitudes towards statistics and achievement behaviors. Recent research has suggested a connection between expectancy value theory and statistics learning (Corwyn & MaGarry, 2020); however, unlike these studies we utilized data of direct measurement of students' attitudes towards statistics. Findings have invaluable implications for practices in statistics classrooms and for designing intervention measures for attitude improvement.

Applying the Expectancy-Value Model to Statistics Attitudes

The expectancy-value model (Eccles et al., 1983) includes two broad constructs, expectancies and value that are broken down into several factors that make up each. Expectancies encompass the factors that lead to a student estimating their likelihood, or expectation, of success if they engage in achievement related behaviors. The students' expectations of success are determined by their self-concept; however, self-concept is developed through a series of experiences and interpretations of those experiences. Students' interpretation and memory of past achievement related experiences as well as their perceptions of others' expectations including interpretations of their stable characteristics through social belief structures (e.g., gender stereotypes of math ability) lead to the development of a self-concept of ability. Their previous achievement related experiences include the grades they earn for assignments, tests or courses, as well as evaluations received when interacting with others (e.g., teachers, parents, peers). Importantly, the interpretations of these experiences are argued to be stronger predictors than the experiences alone, and this is a key feature of the expectancy-value theory. The theory was designed to explain achievement behavior with psychological and developmental factors beyond innate ability. As such, factors such as past achievement related experiences are not by themselves determinant of self-ability and expectancies but mediated by the students' interpretation of those experiences. This is also true of others' expectations of a student and stable characteristics. The students' interpretation of others' expectation and social belief systems mediate the effect of such variables.

In the expectancy-value model, whether a student will engage in achievement related behavior, and the amount of effort they put forward if they do engage, is determined not only by their expectation of success but also the subjective value they place on the various achievement related tasks (Perez et al., 2019). Task value is broken down into four components: 1) interest and enjoyment value; 2) attainment value; 3) utility value; and, 4) relative cost. The first three components have the potential to increase the value of the task while the last, cost, can decrease the value of the task. Cost refers to the invested resources and potential negative consequences of failing. Interest and enjoyment refer to the amount of pleasure engaging in the task will bring to the individual. Attainment value refers to how important success is to the student's self-schema that is their goals and personal values. Utility value, however, is a measure of the importance of the task in reaching a long-term goal. For example, a student who believes they are a good math student may have high attainment value stemming from this self-schema. They believe they are a good math student and therefore will seek to do well in math courses. They may also have high utility value as this would aid them in achieving success in math course. They would therefore invest the time and effort to perform the tasks needed to succeed.

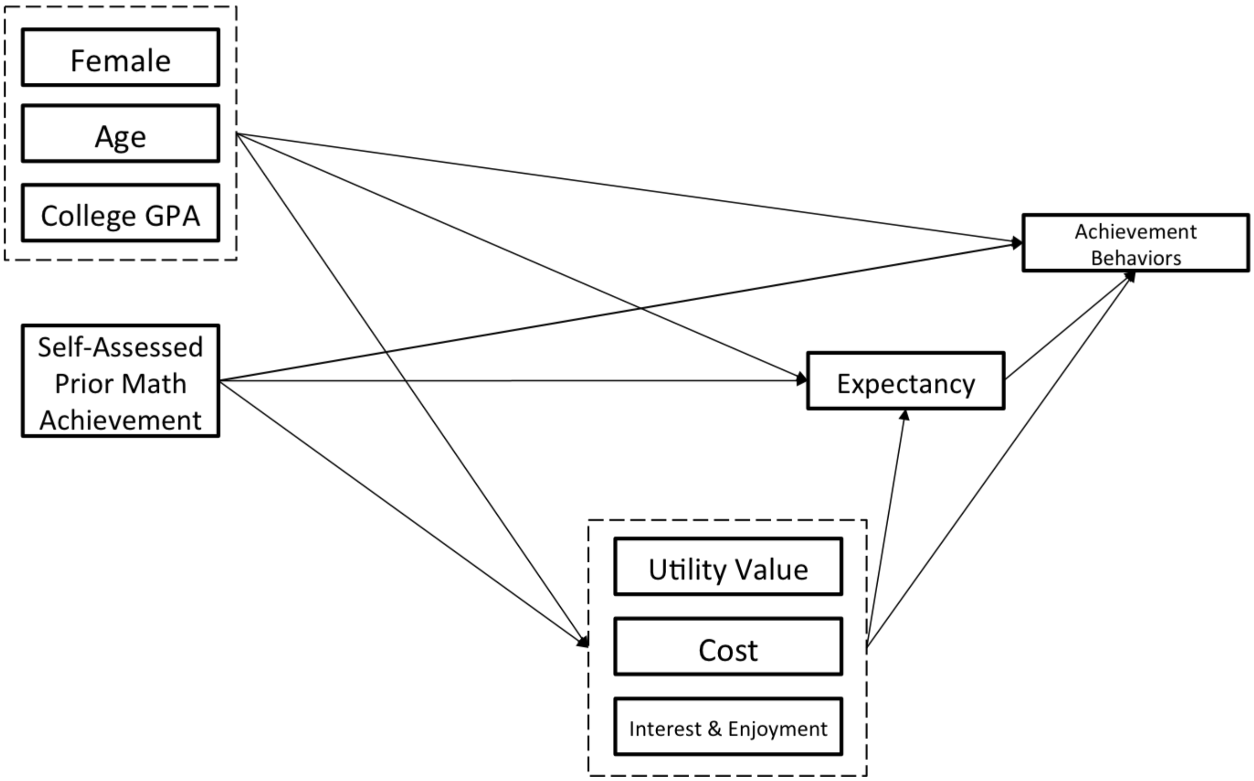

Figure 1. Conceptual Model of Student Effort for a Statistics Course Developed Based on Expectancy-Value Theory.

Attainment value can be challenged if a student feels that the math or statistics course they are taking is not necessarily important for their long-term goal of earning a degree. The overall value that the student has for the task would therefore depend on (1) the students' evaluation of attainment and utility value and (2) whether they believe the task will bring them enjoyment. This would be offset by the students' perception of the potential resources that will be lost by completing the task and the possible negative consequences of failure.

Understanding the mediation of relationships between these factors can allow instructors to better tailor their efforts in the classroom. For example, in the expectancy-value model, the effect of prior achievement related experiences on affective memories and reactions is mediated by a separate construct, the student's interpretations of the experience. Students' interpretation of their previous experiences–particularly in mathematics based courses such as statistics–could play a critical role in shaping their attitudes towards statistics. One interpretation of particular concern would be whether a student believes their past experience is indicative of their innate ability to do well in mathematics and related domains. This type of belief, referred to as a fixed-mindset, has been documented as being related to poor academic outcomes (Dai & Cromly, 2014; Paunesku et al., 2015; Yeager, Romero et al., 2016; Yeager, Walton et al., 2016; Yeager et al., 2019).

Educators would be able to provide better classroom experiences for students if we understand the mediating role of a student's perceptions about their prior experience, and if we can constructively use these perceptions to influence their future performance. For example, one way of addressing the relationship between past performance and achievement in statistics is to provide students with curriculum or assignments that review prerequisite math material. However, if the students' perception of their past performance is important, then efforts should be made to allow students to explore this as well. Otherwise, students' perceptions may be a barrier to their success not only in statistics but also with review assignments. Instructors might consider discussing with students that past performance is not an automatic determinant of future outcomes. For example, Smith and Capuzzi (2019) showed that after a mindset intervention with statistics students, which explored the idea of ability being developed and malleable rather than innate and fixed, having a growth mindset was related to higher course grades.

This is one example of how the relationships posited in the expectancy-value model (Eccles et al., 1983; Wigfield & Eccles, 2000; Figure 1) provide a more comprehensive framework for understanding the relationship between constructs that influence student attitudes and achievement behaviors, and therefore has a greater potential of explaining students' statistics achievement. This may make the expectancy-value model more helpful to guiding practices in statistics classrooms and intervention development.

Another theoretical model that explains statistics attitudes is the Model of Student Attitudes Towards Statistics (SATS-M; Ramirez et al., 2012). This model is an adaptation of the expectancy-value model (Eccles et al., 1983; Wigfield & Eccles, 2000) and focuses on six major constructs: student characteristics, previous achievement related experiences, attitudes towards statistics (affect, value, interest, perceived cognitive competence, and difficulty), effort, and statistics course outcomes. The SATS-M posits that attitudes constructs are simultaneously influenced by past educational experiences and student characteristics, which all directly influence effort, and have no impact on each other or direct relationship with outcomes. We chose to use expectancy-value theory in the present study, as it provides a more comprehensive model that encompasses the various direct and indirect relationships between these factors, and thereby potentially depicts a more accurate framework of statistics attitudes and achievement.

Current Study

The goal of this study was to identify a model that explains the relationship between factors that influence students' attitudes towards statistics and to use this to inform practice in the statistics classroom, particularly with students who are not majoring in statistics. We examined the attitudes of students using data from the most current 36-item Survey of Attitudes Towards Statistics (SATS; Hilton et al., 2004; Schau et al., 1995) to draw insights from the expectancy-value model to better understand the relationship between students' attitudes and their achievement behaviors in a statistics course. One study (Hood et al., 2012) used data from the SATS-28, an earlier version of the instrument, to model the relationship between students' attitudes and statistics achievement using the expectancy-value model as a guide. Our study differs from this work by using an expanded version of the SATS and including additional variables known to influence statistics outcomes such as interest and GPA, Further, to better understand ways that we can increase students engagement in the classroom, we focused on the achievement behaviors as the outcome so as to inform ways that we can develop experiences for students that will increase student engage.

Materials and Methods

Participants and Procedure

The sample included undergraduate psychology majors ($N = 310$) from a small liberal arts school in Southeastern Pennsylvania and a large public school in central Pennsylvania. To participate, students had to have completed or be currently enrolled in a statistics course offered by their psychology department. The course was required for all psychology majors and comprised a yearlong curriculum. Topics included probability and central limit theorem, descriptive analysis, and inferential statistical tests such as *t*-tests, ANOVAs, and correlation and regression. In addition to traditional multiple-choice-question exams, students were also graded on a comprehensive portfolio that required them to conduct analyses using statistical software to answer predetermined research questions and provide written summaries of the results.

The majority of students were female (79.30%) with a mean age of 21.66 ($SD = 3.99$). GPA was coded on a scale of 1-9 with 1 corresponding to a F and a 9 corresponding to an A. Students reported a mean college GPA of 8 ($SD = 1$), equivalent to a letter grade of B and an average rating of 5 (out of 7, $SD = 1.4$) for past math achievement. The mean number of credits completed was 65.47 ($SD = 30.82$) indicating that many students were in their sophomore or junior years. Students reported having completed an average of 3.94 ($SD = 1.20$) mathematics and statistics courses in high school and 2.60 ($SD = 1.34$) mathematics and statistics courses in college.

Students participated in the study during the last two weeks of the semester. They were given time in class to complete a paper-and-pencil questionnaire including demographic questions, items about achievement, and the SATS-36 measure. No incentives were provided. The research was reviewed and approved by the Institutional Review Board at the University where the data were collected. All procedures met the ethical standards outlined by the American Psychological Association (2020).

Measures

The Survey of Attitudes Towards Statistics (SATS-36; Hilton et al., 2004; Shau et al., 1995) was developed to provide both instructors and researchers with a tool that could measure the most important dimensions of students' attitudes towards statistics and would be applicable to students in introductory courses. The original instrument measured was designed using the expectancy-value framework and resulted in subsections that measure four attitude constructs: affect, cognitive competence, difficulty, and value. The SATS was later expanded to include the two additional constructs of interest and effort comprising a total of 36 items.

The SATS-36 was used here to measure the various constructs included in the expectancy-value framework. The measure also included personal characteristic variables such as gender, age and GPA. Past educational experiences was operationalized using one item on student-perceived past math achievement ("How well did you do in mathematics courses you have taken in the past?") on a 7-point Likert scale anchored at 1=very poorly and 7=very well. Thirty-six items measure six subscales: affect, perceived cognitive competence, interest, value, perceived difficulty and effort. Items are positively and negatively worded statements that are rated on a 7-point Likert scale anchored at each end (strongly disagree/agree) and in the middle (neither disagree nor agree). The posttest version of the survey was used. This version uses past tense for several items on the SATS (e.g., *I worked hard in my statistics test*) so that students' responses would reflect their experiences and behaviors during their statistics course. Other questions retain the current tense (e.g., *I can learn statistics*).

Several studies have demonstrated evidence for reliability and validity for both the original version of the survey, the SATS-28, as well as the newer version, the SATS-36 (Cashin & Elmor, 2005; Hilton et al., 2004; Schau et al., 1995; Tempelaar et al., 2007). In the current study, we sought further evidence for the factor structure of the 36 SATS items as administered to our study participants with an exploratory structural equation approach (ESEM; Marsh et al., 2009). Briefly, the ESEM results indicate 5 latent factors underlying a reduced number of items, with some items being excluded from the model due to low factor loadings. The internal consistency is high for the overall measure (α = .829) as well as within the 5 subscales (α's = .701 ~ .920). We present detailed ESEM results in the Results section.

Analytic Approach

We conducted exploratory structural equation modelling of the participants' responses to the SATS-36 questions. ESEM integrates both confirmatory and exploratory factor analyses, thus it examines the theoretical dimensionality of a measure and is flexible in the sense of estimating item cross-loadings (Marsh et al., 2009). ESEM, a more flexible psychometric framework compared to exploratory or confirmatory factor analysis (Cano et al., 2021), is gaining increasing popularity in higher education research and other social science research areas, due to its methodological appropriateness and quantitative rigor (Green, 2016). The choice of ESEM as our approach to measurement validation was based on two considerations specific to the interested measure in the present study. First, although the six-factor structure has been previously tested (Ramirez et al., 2012), a confirmatory factor analysis approach where each item is specified to load on one factor only may lead to poor model fit. Second, it was not clear to us a priori whether the expanded version of the SATS-36 would manifest the 6-dimensional model proposed by Ramirez et al. (2012) as most research conducted using a version of the SATS has used the original 28 item measure (Ramirez et al., 2012). In this study, we use the full 36-item measures. As such, the model would better represent the item-factor relations if we could estimate item cross-loadings, as we were able to do with our ESEM models.

We examined all items with a new ESEM model hypothesizing five factors based on the expectancy-value model—utility value, cost, interest and enjoyment, expectancies and achievement behaviors[1]. With a cutoff of .35 for standardized item-factor loadings, we eliminated the low-loading items from the designated subscales, and, hence, excluded them from further analyses. We then calculated the average item scores within each of the 5 subscales, entered them in a path model to examine the structural relations based on the expectancy-value theory (Wigfield & Eccles, 2002; Figure 1). We decided to use a path model with composite scores instead of using a full SEM approach with both the measurement and the structural parts mainly due to the restrictions posed by our sample size. With our sample of 310 participants, we had just enough statistical power to estimate the current path model. This sample would have been underpowered for estimating a full SEM.

We used Mplus 6 (Muthén & Muthé, 1998-2010) to test the ESEM and path models. We evaluated the model-to-data fit with cutoffs for fit indices suggested by Hu and Bentler (1999). Missing data on all variables in the path model were 0.3~1.0%, except GPA (missing 7.4%). The Little's MCAR test showed that the missing data mechanism was not MCAR (x^2[275] = 326.176, p = .018), however,

[1] Also, we hypothesized six factors consistent with the Model of Student Attitudes Towards Statistics model, however, the ESEM model showed inadequate factor loadings ESEM of responses to the SATS items based on a six-factor model. Further, there was inadequate model-to-data fit (CFI < .96, see Table 1 for ESEM-6; Hu & Bentle, 1999). Three of the six factors had items cross-loaded on multiple other factors, and many items loaded on their hypothesized factor with a standardized loading lower than .35. Overall, the results indicated that the factor structure of the original SATS-36 (Hilton et al., 2004) does not hold. In particular, the constructs affect, cognitive competence, and difficulty were not recovered in our ESEM analysis.

the missingness is believed to be MAR due to its small percentage and partly being accounted for by variables in the model. We used Full Information Maximum Likelihood as the estimation method for all analyses to handle missing data. For ESEM, we used Oblique Geomin rotation—a nonorthogonal-dimension rotation approach—as recommended for ESEM analyses of continuous item-level variables similar to ours.

Results

Factor Structure Shown by ESEM Results

The five-factor model showed an adequate fit to the data with 21 retained items (Table 1 for ESEM-5) and none were highly cross-loaded on multiple factors. The 5-factor solution holds; the standardized item-factor loadings ranged from .473 to .893 (Table 2). We retained the 5-factor model, which provides evidence for construct validity for the reduced SATS measure with 21 items. The factors represented five constructs in expectancy-value theory. Five of the items represented utility value (i.e., "statistics is worthless" and "…have no application…in my profession"). The four items that represented cost were based on the definition of Eccles et al. (1983) to include perceived effort, loss of valued alternatives, or psychological cost associated with tasks. The four cost items included students' perceived effort (i.e., "Statistics requires massive calculations" and "...a new way of thinking") as well as psychological cost (i.e., "I was under stress during statistics class.") Four items represented interest and enjoyment and three items represented students' expectancies for success (i.e., "I can learn statistics"). Finally, four items reflected students' achievement related behaviors in statistics (i.e., completing all assignments, working hard, studying hard and attending every class).

Table 1. ESEM and Path Models Fit Statistics.

Model	# of Para.	AIC	BIC	χ^2 [*df*]	*p*	RMSEA [90% CI]	CFI	SRMR
ESEM-6	209	27929.491	28710.435	425.558 [225]	<.001	.056 [.046, .061]	.949	.035
ESEM-5	137	20992.469	21504.380	223.2 [115]	<.001	.055 [.044, .066]	.966	.022
Path Model	39	4397.346	4539.793	2.496 [1]	.114	.072 [.001, .191]	.992	.014

Note. Para. = Parameters

Table 2. Items Factor Loadings from the ESEM-5 Model, and Subscale Internal Consistency

Item	Standardised Factor Loadings					Cronbach's α
	Expectancy	Utility Value	Interest and Enjoyment	Cost	Achievement Behavior	
06. Statistics formulas are easy to understand.	**.693**	-.023	.011	.074	-.053	.820
31. I can learn statistics.	**.700**	.000	.100	.000	.126	
32. I will understand statistics equations.	**.885**	.086	.002	.009	.040	
07. †Statistics is worthless.	.022	**.772**	.034	-.157	-.049	.867
13.† Statistics is not useful to the typical professional.	-.014	**.717**	-.018	.029	.020	
21.† Statistics conclusions are rarely presented in everyday life.	.025	**.665**	-.120	.064	.045	
25.† I will have no application for statistics in my profession.	-.052	**.796**	-.001	-.042	-.014	
33.† Statistics is irrelevant in my life.	.024	**.826**	.036	-.008	.036	
19. I will enjoy taking statistics courses.	.293	-.054	**.633**	-.029	-.045	.920
12. I am interested in being able to communicate statistical information to others.	-.001	.045	**.752**	-.024	.032	
20. I am interested in using statistics.	.078	.015	**.839**	-.003	-.033	
23. I am interested in understanding statistical information.	-.069	.022	**.893**	.074	.018	
29. I am interested in learning statistics.	.035	-.011	**.871**	.013	.077	
18.† I will be under stress during statistics class.	.257	.158	.039	**.437**	-.104	.701
30.† Statistics involves massive computations.	.010	-.064	.080	**.583**	-.038	
34.† Statistics is highly technical.	-.031	-.083	-.007	**.772**	.021	

36.† Most people have to learn a new way of thinking to do statistics.	.053	.030	-.060	**.636**	.035	
01. I completed all of my statistics assignments.	.238	-.071	-.054	-.023	**.703**	.775
02. I worked hard in my statistics course.	.075	-.006	.019	-.103	**.840**	
14. I studied hard for every statistics test.	-.079	.138	.018	.043	**.660**	
27. I attended every statistics class session.	-.100	.073	.089	.088	**.526**	

Note. All item loadings are significant at $p < .001$. † Item responses coded reversely.

Table 3. Inter-Factor Correlations from the ESEM Model, and Descriptive Statistics of Corresponding Subscale Scores

	Min.	Max.	*M*	*Var.*	Skew.	Kurt.	1	2	3	4	5
Expectancy	1	7	3.523	1.147	0.322	0.438	--				
Utility Value	1	7	4.628	1.940	-0.512	-0.296	.093^{ns}	--			
Interest and Enjoyment	1	7	3.808	2.147	-0.482	-0.093	.477***	.204***	--		
Cost	1	7	3.523	1.147	0.322	0.438	.173**	-.007^{ns}	.190**	--	
Achievement Behaviors	1	7	6.038	0.872	-1.596	3.698	.114^{ns}	.168**	.174**	-.078^{ns}	--

Note. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

As presented in Table 3, we found mostly significant positive correlations between these five factors, except one significant negative correlation between cost and value, and four non-significant correlations—between achievement behaviors and expectancies, achievement behaviors and cost, value and expectancies, and value and cost. All inter-factor correlations estimated in the ESEM model were consistent with the expectancy-value theory, which suggests further evidence for the construct validity (see Table 4 for a corresponding variance-covariance matrix).

Table 4. Covariance-Variance Matrix for the Path Models of Student Effort

	Variable	1	2	3	4	5	6	7	8	9
1	Cost	1.125								
2	Utility Value	-0.114	1.874							
3	Expectancy	0.367	0.143	1.845						
4	Interest and Enjoyment	0.345	0.346	1.073	2.136					
5	Achievement Behaviors	-0.095	0.218	0.174	0.268	0.845				
6	Age	-0.237	-0.18	-0.095	0.663	0.601	15.327			
7	GPA	0.058	0.407	0.109	0.334	0.182	0.357	1.623		
8	Self-Assessed Math Ach.	0.019	0.087	0.396	0.087	0.205	-0.061	0.112	1.957	
9	Female	-0.041	0.031	-0.042	-0.079	0.023	-0.182	0.107	0.007	0.160

A Path Model Based on Expectancy-Value Theory

Effects on Achievement Behaviors

The path model with the five variables (i.e., composite scores on each subscale) based on expectancy-value theory fit the data excellently (see Table 1 for fit indices). As Figure 3 shows, a considerable portion of variance (13% ~ 35%) in the endogenous variables was accounted for by the expectancy-value model. The model parameter estimates showed that motivation variables (i.e., interest and enjoyment and utility value) served as important mediators of the effect of prior achievement on current achievement behaviors in statistics (see Table 5 for direct, indirect, and total effects of student characteristics and self-assessed past math achievement on achievement behaviors).

Table 5. Standardized Direct, Indirect, and Total Effects of Self-Assessed High School Math Achievement, and Individual Characteristics on Student Achievement Behaviors and Expectancy for a Statistics Course Based on the Expectancy-value Model

Path	Total Effect	Direct Effect	Indirect Effect (and Breakdowns)*
Effects on Achievement Behaviors			
Self-Assessed Math Achievement	.135**	.135*	.019ns
Female	.054ns	.07ns	-.016ns
Age	.166**	.152**	.015ns
GPA	.122*	.070ns	.052*
→ Interest and Enjoyment → Achievement Behavior			.035~
→ Utility Value → Achievement Behavior			.030~
Effects on Expectancy			
Self-Assessed Math Achievement	.204***	.187***	.018ns
Female	-.098ns	.006ns	-.104**
→ Interest →Expectancy			-.08**
Age	-.032ns	-.064ns	.032ns
GPA	.073ns	-.044ns	.117***
→ Interest → Expectancy			.107**

Note. * Only significant breakdowns of the significant indirect effects are presented in this table.
~ $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

First, college GPA, although not directly associated with achievement behaviors, was found to have marginally significant indirect effects on achievement behaviors through interest and enjoyment ($\beta = .035$, $p = .06$), and utility value ($\beta = .03$, $p = .08$). Even though each indirect relation was only marginally significant, additively they had a significant total indirect effect on achievement behaviors ($\beta_{indirect} = .052$, $p < .05$), highlighting the fact that interest and enjoyment, and utility value play an indirect but crucial role in influencing achievement behavior in statistics. In other words, the effect of prior GPA on current statistics achievement behaviors was fully mediated by interest and enjoyment as well as utility value: Higher GPA was related to higher interest and enjoyment and higher utility value, and both interest and enjoyment, and utility value were related to more achievement behaviors.

Regarding direct effects on achievement behaviors, self-assessed prior math achievement ($\beta_{total} = .153$, $p < .01$) had a significant positive direct effect on achievement behaviors, which indicates the importance of students' perception of their prior performance and achievement for their current statistics learning. Age also had a significant positive effect on achievement behaviors ($\beta_{total} = .166$, $p < .01$), suggesting better achievement behaviors in statistics by older students.

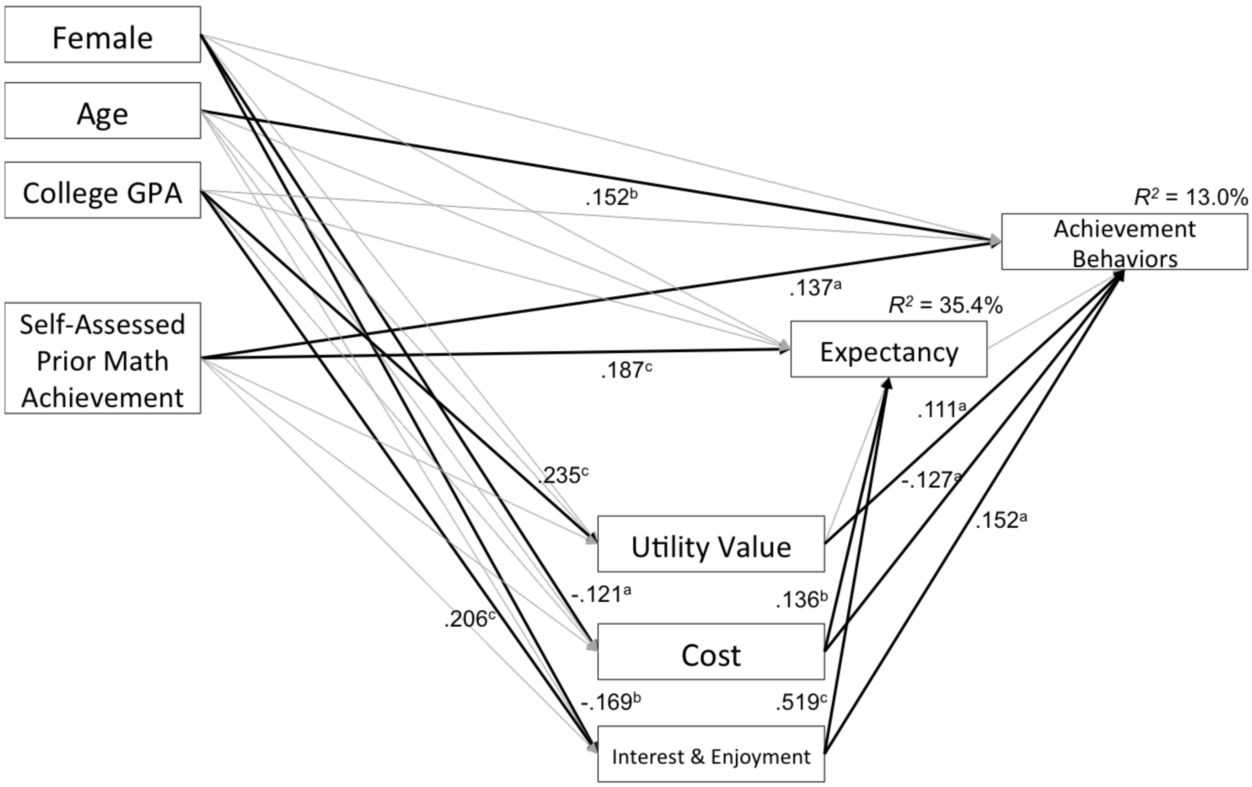

Figure 2. Path Model of Achievement Behaviors for a Statistics Course Based on the Expectancy-Value Theory with Standardized Path Coefficients and Percentages of Variance Explained. *Note.* Nonsignificant paths are in grey. Exogenous variable residual variances and covariances, and endogenous variable disturbances and covariances are omitted from this path diagram.

Effects on Expectancy

Similar to its role in achievement behaviors, college GPA did not have a direct impact on expectancy beliefs, but it showed a significant positive indirect effect through interest and enjoyment, indicating that higher GPA was associated with higher interest and enjoyment, and therefore higher expectancy beliefs ($\beta = .107, p < .01$; Table 5).

Prior research has shown differences in male and females students' attitudes towards math (Watt, 2006). In this study we found that female students had lower expectancy than males, and this difference by gender was also mediated by interest and enjoyment ($\beta = -.088, p < .01$). This finding shows that females tended to find less interest and enjoyment in statistics than males, and interest and enjoyment was positively associated with expectancy, and, therefore, indirectly females had lower expectancy beliefs about their achievement in statistics. The direct association between female and expectancy was nonsignificant. Taking both indirect and direct relations into account, we found that interest and enjoyment fully mediated the association between gender and expectancy beliefs about statistics achievement.

Regarding the direct effects on expectancy beliefs, self-assessed prior math achievement was the only significant variable that had a significant direct effect on expectancy beliefs ($\beta = .187, p < .001$). Again, this suggests the imperative role of students' perception of their prior math achievement in their current expectancy beliefs about statistics achievement.

Discussion

We sought to identify factors that influence student attitudes' towards statistics and its relationships with achievement behaviors among non-statistics majors in a college statistics class. Our findings showed that students had different levels of interest and enjoyment, utility value, expectancy, and perceived cost for statistics learning, and that these variables had significant direct and indirect influences on students' achievement behaviors as hypothesized in the Expectancy-Value framework (Eccles et al., 1983).

Firstly, perceived utility value, and interest and enjoyment mediated the effects of prior achievement (college GPA) on achievement behaviors and expectancy beliefs. Second, perceived cost and interest and enjoyment mediated the effects of gender (being female) on achievement behaviors and expectancy beliefs. Self-assessed prior math achievement was directly positively associated with both achievement behaviors and expectancy beliefs, and age was directly positively associated with achievement behaviors. Among the attitudes and behavior variables, we did not find a direct relationship between expectancy beliefs and achievement behaviors, or one between perceived utility value and expectancy beliefs.

Our findings are to a large extent consistent with the expectancy-value model and prior research that shows interest and enjoyment, utility value, self-assessed prior math achievement and expectancy beliefs are related to achievement and other student outcomes in statistics courses. Interest and enjoyment have been found to be correlated with quiz grades, test grades, (Tempelaar et al., 2007) and course grades (Cashin & Elmore, 2005) in statistics courses. Utility value also has demonstrated a relationship with course engagement and course grades in statistics (Sutter et al., 2022). Students' beliefs about their ability to do well in statistics has also been related to their achievement in statistics (Emmioğlu & Capa-Aydin, 2012). Research shows a direct relationship between past performance both in math courses (Sorge & Schau, 2002; Chiesi & Primi, 2010) and statistics courses (Hood et al., 2012) to be related to statistics achievement as well as achievement behaviors in statistics courses (Hood et al., 2012; Tremblay et al., 2002). Our study adds to this literature by examining some of the more complex relationships between these variables with prior GPA, self-assessed math achievement, and gender in a sample of statistics students who are not majoring in statistics.

Key Findings and Recommendations for Instructional Practices

Research has shown that students' expectations for success are related to their outcomes in statistics (Emmioğlu & Capa-Aydin, 2012); however, we did not find a direct relationship between expectancy beliefs and achievement behaviors. This is in contrast to the expectancy-value theory that posits stronger expectations of success will lead to engaging in more achievement related behavior. Many studies have confirmed a direct relationship between expectancy beliefs and achievement behaviors. The lack of a direct relationship in this study may be in part due to the limitations of the SATS-36 to measure these constructs. For example, achievement behaviors rely on student self-report.

Another possible explanation for the lack of a direct relationship may be the wording/phrasing of the expectancy-beliefs items and the achievement-behavior items. The former are written in the present or future tense, e.g., *I can learn statistics*, and *I will understand statistics questions*. The latter is written in the past tense, e.g., *I worked hard in my statistics test*. Note that the measurement occurred in the last two weeks of the semester, and, therefore, the students were very likely referring to their achievement behaviors specifically in the semester, whereas they referred to a general expectancy of their statistics learning when answering the expectancy-beliefs questions. There seemed to be a mismatch in references led by the writing of the items, which is a limitation of the SATS-36 scale.

We found several indirect effects that have implications for practice. Our findings showed that students with lower prior GPAs, who may be at an increased risk for poor course outcomes, are more likely to believe they are able to succeed in statistics and to have more positive achievement behaviors when they find the statistics course interesting and enjoyable and value the course as more useful. This has direct implications for instruction in statistics. Instructors can consider using pedagogical approaches that have been demonstrated to improve engagement, interest and even attitudes towards statistics overall. For example, instructors can adapt activities that engage their statistics students with real life simulations (Lawson et al., 2003; Schoenfelder et al., 2007; Wiberg, 2009). Carlson and Winquest's (2011) workbook is designed to teach students statistics using guided activities outlined in the workbook. Carlson and Winquest (2001) found that among non-majors taking statistics, students' were more confident about their ability to achieve in the course and liked statistics more after engaging with the workbook. A gamified curriculum that improves students' attitudes such as perceived ability to do well in the course, interest in statistics, and value for the course while simultaneously instructing on statistics is also available (Smith, 2017).

Our findings also suggest that instructors be thoughtful about helping not only students with lower GPAs but also students with negative perceptions of their past math achievement. Self-assessed past math achievement had a direct effect on students' expectations for success and their achievement behaviors in their statistics course. If perceptions of their past performance lead to lower expectations for success and less achievement behaviors, then we need to ensure that we are engaging with these students in a way to communicate clearly to them that their past experiences do not have to limit them from achieving in the course. This communication can also benefit students with lower GPAs who are having difficulty finding value and enjoyment in their statistics course. By emphasizing that their general academic standing does not have to stand in the way of their enjoyment in the course, we may be able to remove this barrier of their engaging in achievement behavior and subsequent success.

One way to accomplish this is through explicit conversations designed to help students change their thinking about their past experiences and achievement. Such conversations may be a direct route to helping students understand that their performance in the course is not predetermined and empowering them with strategies for success. Further, instructors can communicate with students' about their own utility value for statistics as this has been shown to be related to students' perception of how useful statistics is to them (Han et al., 2019).

Instructors can consult the literature for guidance on different ways to incorporate explicit conversations about the role of past experiences and achievement in statistics course outcomes (Acee & Weinstein, 2010; Lai et al., 2018; Smith & Capuzzi, 2019). For example, Acee and Weinstein (2010) incorporated messages into a statistics course about the importance and value of statistics and found improvement in students' attitudes which was in turn related to higher academic achievement. Smith and Capuzzi (2019) developed a mindset intervention specifically for non-major statistics courses. The intervention includes a presentation on the way in which students' beliefs about their mathematical ability is influenced by culture and debunks the myth that only some students are capable of high achievement in math using current neuroscience findings. Students receiving the intervention were more likely to hold a growth mindset and in turn had lower anxiety and higher course grades. There is also preliminary data to suggest that this approach can work well with non-major graduate students taking statistics (Lai et al., 2018).

The approaches we have listed here have been demonstrated to help students with lower academic achievement levels perform more strongly making them an appropriate choice for students with lower prior achievement. However, when implementing these approaches, instructors should be cautious of their own beliefs regarding their students as instructors' judgements about students' past achievement has been demonstrated to be related to students' achievement, expectations of success and aspirations (Zhu, 2018).

Research on ways to adapt the classroom to improve statistics outcomes is not new (e.g., Goldfinch, 1996). Several pedagogies that have been shown to increase interest and enjoyment in a course include problem-based, student centered, and gamified curriculums. A plethora of resources exist to provide guidance on implementing these pedagogies in the statistics classroom including peer reviewed articles, journals and edited books dedicated to the teaching of statistics (see Beyer & Peters 2020; Dunn et al., 2007; Smith, 2017). Based on the results of this study, these approaches may be beneficial for statistics instructors to use in courses with non-majors as they may improve the students' interest and enjoyment and lead to positive achievement behaviors. These approaches are also in line with recommendations from Guidelines for Assessment and Instruction in Statistics (GAISE, 2016) to teach statistics in a way that uses real data, context and active learning.

The findings of this research also show that particular attention should be paid to female students taking statistics courses. Many majors that require a statistics course have large numbers of female students including psychology, nursing and education. Female students have been shown to have low expectations for math outcomes (Kyttala & Bjorn, 2010) and in this study also had lower expectations for success. Together, the lower expectations for success, higher perceptions of difficulty and lack of confidence make female statistics students vulnerable to performing poorly in statistics. As such, the achievement behaviors of female students who struggle with math and find statistics difficult will be critical in helping them be successful in statistics. Further, students' perceptions of their past performance (Bornholt, 2001) and having lower value for math (Yumusak et al., 2007) can guide their decision around continued study with math This could make introductory statistics a barrier for female students to persist in programs that require additional statistics course work. The strategies described above can be used to help female students redefine their expected abilities. Female statistics students can learn from their instructor that ability in statistics is not based on static innate traits but rooted in trial and error and seeking helpful feedback to guide such practice.

Limitations and Future Research

The data collected in this study relied on self-reported GPA and past math achievement. Using objective assessments for GPA and assessments of achievement could strengthen results. Achievement behaviors could also be more objectively assessed for example by recording class attendance and assignment completion. Our analyses were restricted by the sample size of 310 participants. The use of path models of observed composite scores could to some extent result in attenuation of path values given the inclusion of measurement error in the manifest variables. Future research should consider enhancing statistical power with a larger sample to estimate a full SEM with both measurement and structural parts.

Future research could focus on the expansion of the SATS-36 to capture other expectancy-value factors not examined in this study. Several individual items on the SATS-36 may be able to be improved in terms of their mapping onto specific expectancy-value constructs. For example, rather than items focusing on efficacy (i.e., "I can learn statistics") it may be better for additional items that address expectations for success to do well in the course (i.e., "I will understand statistics"). Such revisions to the SATS-36 may allow for better modelling of the expectancy-value constructs and subsequently the relationship between the constructs. We did not find a direct relationship between expectancies and achievement related behaviors, which is contrary to the larger expectancy-value literature. This could be a manifestation of the way in which the SATS-36 operationalizes expectancies. Future research could also expand our model by including the potential change in constructs over time. Research has shown that several constructs in the expectancy-value model are not static (Johnson et al., 2014; Perez et al., 2019).

We suggest implementing pedagogy and curriculum that can directly impact the achievement behaviors, but we also recommend integrating instructional practices and pedagogy that enhance interest, enjoyment, perceived utility value and expectancy beliefs as indirect ways to promote positive achievement behaviors. Examining these outcomes using a randomized design would allow for a better understanding of the extent to which psychology students' interest, enjoyment, and utility value, particularly for low GPA and female students, can be positively influenced. Further, the findings could shed light on the effect these potential increases could have not only achievement behaviors but also course outcomes.

Conclusion

Overall, the numerous indirect effects we observed in this study highlight that the factors impacting the achievement behaviors of non-major statistics students is complex and a holistic model is needed to understand their relationships. Our data support the idea that the expectancy-value model can provide that holistic framework. The SATS-36 is a useful tool for collecting data from statistics students to model expectancy-value theory, but room for improvement does exist. Finally, the role of interest and enjoyment, and utility value should not be underestimated in terms of its relationship with psychology students' achievement behaviors in statistics. Pedagogy and curriculum should take this into consideration and work to address the low levels of interest and/or value psychology students have for statistics, and this is particularly important for students with lower GPAs or poor past achievement.

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