Impact of Engineering Students' Attitudes on Achievement in Statistics: A Structural Model

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Abstract

We created, tested, and revised a structural model interrelating undergraduate engineering students' previous academic success, their attitudes toward statistics, and their achievement in a required introductory statistics course. Our model was based primarily on Eccles and colleagues' application of expectancy-value models of behavior to mathematics achievement. In the original Saturated Model, students' previous academic success (Previous Success) was an exogenous latent variable. It was followed, in order, by the endogenous latent attitude variables of students' perceptions of the difficulty of statistics as a domain of study (Difficulty), their self-concept about their statistical knowledge and skills (Cognitive Competence), their feelings toward statistics (Affect), and their perceptions of the value of statistics (Value). All of these latent variables were allowed to impact the outcome latent variable of Achievement both directly and indirectly through all possible downstream paths. Although this model fit the data reasonably well, several paths (including the path from Value to Achievement) were not statistically significant and so were eliminated to create the Pruned Model. The Pruned Model represented the data in a more parsimonious manner with no fit degradation. The amount of variance in each of the latent constructs accounted for by their upstream latent predictors was sizable. About two-thirds of the shared variance in Achievement was associated with the impact of Previous Success, while the remaining one-third was associated with the impacts of the upstream latent attitude variables of Difficulty, Cognitive Competence, and Affect. Our results support a model in which both prior academic achievement and attitudes toward statistics impact engineering students' achievement in introductory statistics courses.

Impact of Engineering Students' Attitudes on Achievement in Statistics: A Structural Model

Successful completion of at least one statistics course is a requirement in many post-secondary programs. Students often view these courses as overwhelming learning and survival tasks that cause a great deal of stress (e.g., Onwuegbuzie and Daley 1999). Instructors and students alike believe that students' attitudes toward statistics impact their statistics achievement and even their willingness to try to complete these courses. Attitudes toward statistics affect a large number of students in their college (and eventually professional) careers (Young and Nelson 1994; Gordon 1995; Potter 1995; Green and Carney 1997; Loftsgaarden and Watkins 1998; Wilson 1998; Parker, Pettijohn and Keillor 1999).

Until recently, most studies exploring attitudes toward statistics have focused on a small part of the complex relationships between attitudes and achievement. These studies often have explored these relationships by correlating attitude and achievement scores. Most studies report small to moderate correlations between attitudes toward statistics and statistics course achievement with better attitudes associated with higher achievement. At least some of the variability in findings is due to differences in samples (e.g., community college, undergraduate, or graduate students), attitude instruments (a variety of surveys), attitude component measures (e.g., anxiety toward statistics, statistics' value), achievement measures (usually test scores or course grades), and measurement timing (beginning, middle, or end of the course). See Gal, Ginsburg, and Schau (1997) and Harris and Schau (1999) for brief summaries of this research.

However, two groups of researchers have created structural models representing possible causal relationships among these variables. The models generally have addressed the impact of attitudes toward statistics on success in statistics courses and were tested using structural equation modeling (SEM) techniques.

Lalonde and Gardner (1993) developed and tested a model of introductory statistics achievement based on Gardner's theory of second language learning. Tremblay, Gardner, and Heipel (2000) then revised that model and tested it with 166 Canadian students enrolled in five sections of a required introductory course in psychological statistics. Their achievement outcome variable was students' scores on the final exam. Their final model included five exogenous variables: the global construct of aptitude (previous achievement in math and psychology) and scores on four variables (attitude toward the professor, attitude toward the course, interest in psychology, and interest in math). Three endogenous constructs included statistics anxiety and valence (value of statistics) and score on a variable of motivational intensity (effort). The model did not include a direct effect from valence to achievement or between valence and anxiety. The fit of the model was acceptable.

This model included two variables specific to psychology and so cannot be applied directly to students who are not enrolled in psychological statistics courses. However, the results suggested some potentially generalizable findings. Aptitude exhibited the expected strong positive direct impact on achievement and a small negative direct impact on anxiety. Anxiety showed a moderate negative direct effect on achievement. The direct effect from motivational intensity to achievement was positive but quite small.

Wisenbaker and colleagues (e.g., Wisenbaker and Scott 1997; Wisenbaker, Scott and Nasser 1999; Wisenbaker, Scott and Nasser 2000) also created, tested, and modified structural models of statistics achievement. Their models always included achievement and four components of students' attitudes toward statistics (students' feelings about statistics, their self-concept about their statistical knowledge and skills, the value they attributed to statistics, and the difficulty of statistics) assessed twice (pre and post). Some of their models also included mathematics achievement, anxiety, and attitudes as exogenous variables. In their models, the structure interrelating the attitude components differed depending on time of measurement. Participants came from the

U.S. and Israel and were enrolled in undergraduate or graduate introductory statistics courses taught either in a one-semester format or during summer school. Their largest sample consisted of 136 U.S. undergraduates. In general, Wisenbaker and colleagues reported that attitude components measured at the end of the course predicted final course achievement; those measured at the beginning of the course did not.

The purpose of our study was to examine possible causal relationships among undergraduate engineering students' previous academic success, their attitudes toward statistics, and their achievement in a required introductory statistics course. We created, tested, and revised a structural model interrelating these global constructs.

METHODOLOGY

Theoretical Framework

The model created in this study was based primarily on Eccles and colleagues' application of expectancy-value models of behavior to mathematics achievement (e.g., Eccles, Adler, Futterman, Goff, Kaczala, Meece, and Midgley, 1983, Eccles and Wigfield 1995). They posited an important influence of three expectancy-value factors on math achievement. These factors included: (1) students' expectancies for success, (2) their perceptions of task difficulty, and (3) their perceptions of task value. The factor of expectancies for success concerned students' self-concepts regarding their ability to do math successfully. The factor of task difficulty, as its name suggests, referred to students' perceptions of the difficulty of math. The factor of task value reflected students' perceptions of the value of doing math successfully (Eccles and Wigfield 1995). Perceptions of past academic performances influenced each of these three factors.

Statistics Attitudes-Achievement Structural Model

Our Statistics Attitudes-Achievement Saturated Model included six latent constructs (see Figure 1). Statistics achievement (called Achievement in the Model) was the outcome latent variable. Students' reports of their previous academic achievement (called Previous Success), the exogenous variable, represented their perceptions of outcomes from prior learning experiences.

The four endogenous attitudes' latent constructs were based on our application and modification of Eccles and colleagues' three expectancy-value factors. The first attitudes' construct, Difficulty, represented the factor of task difficulty. Eccles and colleagues assessed task difficulty as the student's perception of the difficulty of math for that specific student; we, however, asked for students' attitudes about the difficulty of the domain of statistics for most people. The second attitudes' construct, Cognitive Competence, represented the factor of students' expectancies for success in statistics. Cognitive Competence represented students' perceptions regarding whether they possessed the knowledge and skills needed to learn statistics. The third attitudes' construct, Affect, represented students' positive and negative feelings about statistics. Although Eccles and colleagues included affective perceptions within the factor of task value, we included it in our model as a separate construct for three reasons. First, conceptually, students' affective feelings toward statistics are not the same as their attitudes about the value of statistics. In fact, Eccles and Wigfield (1995) indicated that students' affect influences their perceptions of task value through classical conditioning mechanisms. Second, measures of attitudes toward statistics historically have included this component (often in the form of statistics anxiety). Third, statistics instructors and students believe that students' affect toward statistics is important in its own right. Our fourth attitudes' construct, Value, represented the factor of task value: students' attitudes about the value of statistics.

Eccles and Wigfield (1995) described five directional impacts among their three expectancy-value factors (i.e., Affect impacts Value, Cognitive Competence impacts Affect and Value, and Difficulty impacts Cognitive Competence and Value). We used their directional impacts to interrelate the constructs in our structural model and then filled in the remaining path from Difficulty to Affect to create the Saturated Model. In the Saturated Model, Previous Success was an exogenous latent variable. It was followed, in order, by the endogenous latent attitude variables of Difficulty, Cognitive Competence, Affect, and Value. All of these latent variables were allowed to impact the outcome latent variable of Achievement both directly and indirectly through all possible downstream paths. See Figure 1.

Our Statistics Attitudes-Achievement Model represents a next step in exploring the causal relationships between statistics attitudes and achievement. It clearly is not the only possible or reasonable model.

Methods

Participants

The participants were engineering students enrolled in a required introductory statistics and probability course at a major Southwestern University during the fall semester of 1999 and the spring semester of 2000. Engineering students are rarely studied in regard to statistics education; yet they are an interesting group because of their strong backgrounds in mathematics.

Two sections were offered each semester. Students were from classes taught by three different professors. The course consisted of a lecture section that met twice each week and a lab section that met once each week. The lab section included active data generation and learning exercises, demonstration and use of software, and problem solving with discussion (Hubele 1999). The course covered the usual introductory topics of descriptive and inferential statistics and their applications in engineering problem solving.

Two hundred sixty-four students participated in our research. This sample contained 177 (67%) males and 87 (33%) females. Of these students, 168 (64%) reported themselves as White American, 1 (0.4%) as Native American, 7 (3%) as African American, 18 (7%) as Hispanic American, 34 (13%) as Asian American and 36 (14%) as foreign students. Participants ranged in age from 16 to 55 years, with a median age of about 22 years. Ninety two percent of the participants were between 18 and 30 years old.

Measures

Survey of Attitudes toward Statistics for Engineers (SATS-E).

The SATS-E was based on the Survey of Attitudes toward Statistics (SATS). The SATS was designed to assess four components of attitudes toward statistics as well as other constructs including prior academic achievement (Schau, Stevens, Dauphinee and Del Vecchio 1995). The SATS can be found on the web at www.unm.edu/~cschau/infopage.htm.

The SATS' four-factor structure for attitudes toward statistics was supported for pre-course data collected from a sample of undergraduate students attending a major Southwestern university (Schau et al. 1995). With two minor exceptions, this four-factor structure was invariant across gender for a White subsample from this original sample (Dauphinee, Schau and Stevens 1997).

The SATS was initially developed for students enrolled in introductory statistics courses. It was modified for engineering students enrolled in statistics and probability courses by replacing the term “statistics” with “statistics and probability” in each item. The modified SATS was called the SATS-E.

The four attitude components in the SATS-E were assessed using 28 Likert items with a 7-point response scale that ranged from 1 (strongly disagree) though 4 (neither agree nor disagree) to 7 (strongly agree). These four components included Affect (6 items), Cognitive Competence (6 items), Value (9 items), and Difficulty (7 items).

Affect was defined as students’ positive and negative feelings concerning statistics. An example Affect item is “I will feel insecure when I have to do statistics and probability problems.”

Cognitive Competence was defined as students’ attitudes about their intellectual knowledge and skills when applied to statistics. An example item is “I can learn statistics and probability.”

Value was defined as students’ attitudes about the usefulness, relevance, and worth of statistics in personal and professional life. An example item is “Statistics and probability should be a required part of my professional training.”

Difficulty was defined as students’ attitudes about the difficulty of statistics as a subject. An example item is “Statistics and probability formulas are easy to understand.”

Students’ perceptions of their prior academic achievement were assessed with three questions contained in the SATS-E. These questions asked students about their high school math courses, math self-concept, and current grade-point average.

Statistics Achievement.

Achievement was measured using the teacher-created course assessments including quizzes, a midterm exam, and a final exam. The three types of assessments included short answer and true-false items. Both types of items primarily asked students to apply formulas and concepts and to interpret graphs and outcomes.

Procedures

As part of a larger project, students responded to the SATS-E items over the web outside of class during an eight-day period at the end of the semester. Our website incorporated web survey design recommendations found in the literature. The instructors provided student achievement data after the course was completed. The Institutional Review Boards from the two participating universities approved this project. Students gave informed consent. They received a minimal number of extra credit points for their participation.

Analyses

All SEM analyses were conducted with AMOS 4.0 using maximum likelihood estimation.

Missing Data.

Five of the 264 students each left one item blank while three students failed to report a grade point average. Thus, less than .01% of the data were missing. Kline (1998) suggested that substitution of a group’s mean value is supported when the proportion of missing data is less than 10%. The mean value across the missing attitude or grade point average item for the respondent's gender group was substituted for each of the missing values; ethnicity could not be considered in the mean calculations due to the small sample sizes for some ethnic groups.

Observed and latent variables.

All observed variables except those used in the Achievement latent construct were taken from students' responses to the SATS-E. The latent variable of Previous Success was defined by students' responses to three items assessing prior academic achievement: (1) performance in high school math courses (well), (2) self-concept regarding math (good), and (3) current grade point average (gpa).

For the attitudes' items, responses to each negatively worded item were reversed so that higher scores always meant more positive attitudes. To avoid possible problems associated with non-normality of response distributions for individual Likert-scale items, items within each of the four attitude components were grouped into parcels that served as the observed indicators for their respective latent attitude components. The latent constructs of Affect, Difficulty, and Cognitive Competence were represented by students' mean scores on two parcels of items assessing each of the relevant constructs. Students' mean scores on three parcels of items represented the latent construct of Value. See Dauphinee, et al. (1997) for a description of the SATS items used in each parcel.

The Achievement latent construct was defined by three observed variables. They included students' mean percent correct score on quizzes (quizpct) and their scores on the midterm (midpct) and final (finalpct) exams. We had hoped to also use project scores as a fourth observed Achievement variable. However, project scores exhibited two statistical problems and so were not included. First, students worked on the projects in small groups so the scores were not independent of group membership. Second, project scores showed little variation; most students scored highly on their projects.

For means, standard deviations and correlations between observed variables see the Appendix.

Analysis Approach.

The structural analyses proceeded in two global steps. First, the measurement models for the latent constructs were estimated and evaluated. Second, the Statistics Attitudes-Achievement Structural Model relating the latent constructs was estimated, evaluated, and revised.

Measurement Models

The Measurement Model for each of the latent constructs was tested separately for adequate model fit. For example, the measurement model for the Previous Success latent construct was tested by itself unconnected to other latent constructs. In each model, the factor loading values relating the latent variable to its observed indicator variables were examined for size and direction.

A Baseline Measurement Model was then estimated including all latent constructs, which were allowed to correlate. Because outlying scores can unduly affect statistical results, the Baseline Measurement Model was estimated three times: with outliers included, with outliers eliminated, and with outliers reset to three standard deviations from their mean in the direction of their scores.

Structural Models

The Saturated Statistics Attitudes-Achievement Structural Model was estimated. Because some of the paths connecting the latent constructs in the Saturated Model were small relative to their variability and so were not statistically significant, they were eliminated and the Model was re-estimated. This new model was called the Pruned Statistics Attitudes-Achievement Model.

Results

Measurement Model

Outlying scores did not impact the Baseline Measurement Model in any substantive manner so they were retained in the analyses. This Model fit the data reasonably well, $\chi^2(75) = 157.77$, $p < .0005$, $\chi^2/df = 2.10$, $GFI = .93$, $TLI = .94$, $CFI = .96$, $RMSEA = .065$. Each factor path loading was statistically significant, positive and at least moderate in size. Each latent construct had at least one indicator variable with a path loading greater than 0.80. See Table 1 for the unstandardized factor path loadings (and for the reference variables used in the model). The covariance estimates for the Baseline Measurement Model are provided in Table 2. All covariance values except three were statistically significant; these three included the relationships between Previous Success and Difficulty, Previous Success and Value, and Difficulty and Value.

Table 1: Baseline Measurement Model (Unstandardized Results)

	Indicator Variable	Estimate*	S.E.	C.R.**
Previous Success	well	1		
	good	1.07	0.25	4.30
	gpa	1.12	0.23	4.86
Difficulty	diff1	1		
	diff2	1.06	0.09	11.48
Value	value3	1		
	value2	0.88	0.05	19.43
	value1	0.66	0.04	15.89
Affect	affect2	1		
	affect1	1.19	0.07	16.30
Achievement	quizpct	1		
	midpct	1.11	0.12	9.16
	finalpct	1.12	0.10	11.12
Cognitive Competence	cog1	1		
	cog2	1.45	0.12	12.13

*Path loadings of observed referent variables were set to 1.
**A critical ratio value greater than 1.96 indicates statistical significance at $p<.05$.

Table 2: Measurement Model Covariances

Variable Pairs	Covariance Estimate	S.E.	C.R.*
Previous Success – Difficulty	0.04	0.03	1.65[x]
Previous Success – Cognitive Competence	0.06	0.03	2.31
Previous Success – Affect	0.09	0.03	2.67

Previous Success – Value	0.04	0.03	1.12[x]
Previous Success - Achievement	2.82	0.70	4.03
Difficulty – Cognitive Competence	0.38	0.06	6.53
Difficulty – Affect	0.49	0.07	7.00
Difficulty – Value	0.03	0.08	0.40[x]
Difficulty –Achievement	2.96	0.66	4.48
Cognitive -Competence Affect	0.57	0.07	7.92
Cognitive -Competence Value	0.32	0.07	4.79
Cognitive Competence- Achievement	3.04	0.58	5.27
Affect -Value	0.63	0.09	6.73
Value – Achievement	2.10	0.90	2.35
Affect –Achievement	4.99	0.76	6.55

*A critical ratio value greater than 1.96 indicates statistical significance at $p < .05$.
[x] This relationship was not statistically significant.

Figure 2 presents the standardized parameter estimates for the Baseline Measurement Model. Correlations between latent variables ranged from .03 (between Difficulty and Value) to .91 (between Cognitive Competence and Affect).

Saturated Structural Model

The next step was to estimate the Saturated Structural Model with directional paths replacing the covariance paths between the latent constructs found in the Measurement Model. As must be the case, the Saturated Structural Model yielded fit index values identical to those obtained with the Baseline Measurement Model. Thus, the Saturated Model fit the data reasonably well (see Table 3). However, eight of the 15 direct paths relating the latent constructs were not statistically significant. The parameter estimates of the regression weights relating the latent constructs to their observed indicators and the direct relationships between pairs of latent constructs are presented in Figure 1 (standardized) and in Table 4 (unstandardized).

Table 3: Fit Indices for Structural Models

Model	χ^2	df	p	χ^2/df	GFI	TLI	CFI	PRATIO	MECVI	RMSEA
Saturated	157.77	75	.000	2.10	.929	.939	.956	.714	.964	.065
Pruned	167.05	81	.000	2.06	.925	.941	.955	.771	.951	.064

Table 4: Unstandardized Regression Weights for Saturated Model

Variable Pair	Regression Weight	S.E.	C.R.*
Latent Construct Pair:			
Previous Success - Difficulty	0.33	0.18	1.81[x]
Previous Success – Cognitive Competence	0.24	0.12	2.01

Previous Success - Affect	0.12	0.13	0.93[x]
Previous Success - Value	-0.25	0.25	-1.01[x]
Previous Success - Achievement	16.84	2.96	5.69
Difficulty – Cognitive Competence	0.49	0.06	7.66
Difficulty - Affect	0.08	0.09	0.93[x]
Difficulty - Value	-0.70	0.16	-4.29
Difficulty -Achievement	-0.57	1.38	-0.41[x]
Cognitive Competence-Affect	1.14	0.14	8.17
Cognitive Competence-Value	-1.00	0.68	-1.47[x]
Cognitive Competence- Achievement	-6.46	5.14	-1.26[x]
Affect -Achievement	10.26	4.97	2.06
Affect -Value	1.90	0.52	3.64
Value - Achievement	-1.90	1.13	-1.69[x]
Latent-Indicator Pair:			
Previous Success- well	0.94	0.22	4.31
Previous Success- good	1		
Previous Success- gpa	1.05	0.18	5.88
Difficulty -diff2	1		
Difficulty-diff1	0.94	0.08	11.41
Cognitive Competence-cog1	1		
Cognitive Competence-cog2	1.45	0.12	12.04
Affect -affect2	1		
Affect -affect1	1.19	0.07	16.13
Value-value3	1		
Value-value2	0.88	0.05	19.31
Value-value1	0.66	0.04	15.69
Achievement-quizpct	1		
Achievement-midpct	1.11	0.12	9.16
Achievement-finalpct	1.12	0.10	11.08

*A critical ratio value greater than 1.96 indicates statistical significance at $p < .05$.
[x]This path weight was not statistically significant.

In the Saturated Model the amount of variance in each of the endogenous latent constructs accounted for by their upstream latent predictors was sizable. Value (54% of its variance) and Cognitive Competence (45% of its variance), however, were less well predicted by their upstream latent variables than were Affect (84%) and Achievement (82%). About 55% of the shared variance in Achievement was associated with the impact of Previous Success, while the remaining 45% was associated with the impacts of the four attitude constructs.

For purposes of interpretation, we considered effect values from about 0.20 to 0.34 as small, about 0.35 to 0.49 as moderate, and over 0.50 as large. We did not interpret direct effects that were not statistically significant or any effect that was less than about 0.20. We selected these values based on reasonable assumptions about the importance of changes of these sizes in statistics attitudes and achievement. Based on the standard deviations of the indicator variables in their own scales, small effects corresponded to changes in achievement from about 2% to 6% (depending on the assessment measure), moderate effects from about 4% to 10%, and large effects over

6% to 10%. For attitudes, small effects corresponded to changes on the 7-point scale from one-fifth to one-third of a point, moderate effects from one-third to one-half of a point, and large effects over one-half of a point.

Several of the latent variables in the Saturated Structural Model impacted other variables through multiple paths. Examination of the patterns of impact can yield important information about any model. For example, Difficulty impacted Value directly as well as indirectly through Cognitive Competence and Affect. Difficulty's total effect on Value was the sum of these two effects (the direct and indirect effects). Difficulty had a negative direct effect (-.495) and a positive indirect effect (.512) on Value. The sum of these two effects (.017) represented the net impact of Difficulty on Value. The total effect was negligible while both the direct and indirect effects were large. Table 5 presents the direct, indirect, and total effects for the Saturated Model.

As shown in Table 5, the largest impact by far from Previous Success on any downstream variable was its large positive direct effect on Achievement. An increase of one standard deviation in Previous Success scores resulted in a direct increase of about two-thirds of a standard deviation in Achievement scores. Students who reported higher previous achievement were higher achievers in their introductory statistics course. The direct impacts of Previous Success on the four attitude components were negligible.

Table 5: Standardized Direct and Indirect Effects for Saturated Model

	Effect	Difficulty	Cognitive Competence	Affect	Value	Achievement
Previous Success	Direct	.144[x]	.138	.051[x]	-.078[x]	.682
	Indirect		.092	.206	.160	.118
	Total	.144	.230	.257	.083	.800
Difficulty	Direct		.640	.077[x]	-.495	-.052[x]
	Indirect			.544	.512	.309
	Total		.640	.621	.017	.256
Cognitive Competence	Direct			.850	-.544[x]	-.456[x]
	Indirect				1.178	.671
	Total			.850	.643	.215
Affect	Direct				1.386	.974
	Indirect					-.611
	Total				1.386	.364
Value	Direct					-.247[x]
	Indirect					
	Total					-.247

[x]This direct effect was not statistically significant.

Difficulty exhibited a large positive direct impact on Cognitive Competence of about two-thirds of a standard deviation. It also showed a large positive indirect effect on Affect (about one-half SD). As mentioned above, its total impact on Value was negligible, due to a large negative direct effect coupled with an equally large positive indirect effect. Its impact on Achievement was positive, indirect, and small (about three-tenths SD).

Cognitive Competence exhibited a large positive direct impact on Affect (almost nine-tenths SD). It also exhibited a large positive indirect impact on Value (over one SD) and a large indirect impact on Achievement (about two-thirds SD).

Affect exhibited a large positive direct effect on Value (about one and one-third SD). It also exhibited a large positive direct effect and a moderate negative indirect effect on Achievement; its total impact was large and positive (about two-thirds SD).

Surprisingly, Value's impact on Achievement was small and not statistically significant.

Pruned Structural Model

Eight of the structural regression weights in the Saturated Structural Model were small in relationship to their variability and so were not statistically significant. To continue our exploration of the impacts of statistics attitudes on achievement, these paths were eliminated to create the Pruned Structural Model. See Figure 3. In this Model, Difficulty joined Previous Success as an exogenous variable; they were allowed to correlate. Value joined Achievement as an outcome variable; their errors were allowed to correlate, an approach described by Maruyama (1998) that allows endogenous variables to correlate without assigning causal priority. Cognitive Competence, Affect and Value remained endogenous. In comparison to the Saturated Model, the Pruned Model represented the data in a more parsimonious manner with no fit degradation ($\Delta\chi = 9.28$, $\Delta df = 6$, $p = 0.16$; see Table 3 for other fit index values). See Table 6 for the unstandardized regression coefficients. All, of course, were statistically significant.

Table 6: Unstandardized Regression Weights for Pruned Model

Latent Pairs	Regression Weight	S.E.	C.R.
Previous Success-Cognitive Competence	0.23	0.11	2.10
Previous Success-Achievement	17.48	2.86	6.12
Difficulty-Cognitive Competence	0.51	0.06	8.06
Difficulty-Value	-0.72	0.14	-5.31
Cognitive Competence-Affect	1.24	0.11	11.25
Affect-Value	1.15	0.13	8.88
Affect- Achievement	3.86	0.61	6.31

In the Pruned Model the amount of variance in each of the endogenous latent constructs accounted for by their upstream latent predictors again was sizable. Value (44% of its variance) and Cognitive Competence (49% of its variance) again were less well predicted by the upstream latent variables than were Affect (81%) and Achievement (76%). About two-thirds of the shared variance in Achievement was associated with the impact of Previous Success, while the remaining one-third was associated with the impacts of three attitude constructs.

Table 7 contains the direct, indirect, and total effects for the Pruned Model. Latent construct paths that were eliminated to form the Pruned Model are indicated with a dash.

Table 7: Direct and Indirect Effects Pruned Model

Latent Construct	Effect	Cognitive Competence	Affect	Value	Achievement
Previous Success	Direct	0.132	--	--	0.71
	Indirect		0.119	0.101	0.045
	Total	0.132	0.119	0.101	0.755
Difficulty	Direct	0.665	--	-0.506	--
	Indirect		0.599	0.508	0.244
	Total	0.665	0.599	0.002	0.224
Cognitive Competence	Direct		0.901	--	--
	Indirect			0.763	0.336
	Total		0.901	0.763	0.336
Affect	Direct			0.848	0.373
	Indirect				
	Total			0.848	0.373

In general, the impacts of upstream latent constructs on their downstream latent constructs were similar to those reported for the Saturated Model. The magnitude of some of the effects changed, although in general not enough to change their qualitative size interpretation.

However, two size interpretations did change. Previously the indirect impact of Cognitive Competence on Achievement was large; in the Pruned Model, this indirect impact stayed positive but now was small, about one-third of a standard deviation. In addition, Affect's direct impact on Achievement remained positive but now was moderate, rather than large, in size (about four-tenths SD).

Discussion

The results from the Baseline Measurement Model showed that the indicator variables represented the latent constructs well. Our data fit both the Saturated and the Pruned Statistics Attitudes-Achievement Structural Models reasonably well. The Pruned Model was more parsimonious and so is the preferred Model. In the ideal world, we would have validated the Pruned Model with a different sample of students. Unfortunately, as is often the case in field-based research, we lacked a second sample to do so. Future research is needed to verify the Pruned Model.

At least four findings merit further consideration. First, perhaps the most puzzling disagreement between our results and Eccles and colleagues' expectancy-value model (as well as, we believe, with statistics instructors' beliefs) was the lack of a relationship between Value and Achievement for engineering students. Their expectancy-value model predicted that an increase in Value should lead to an increase in Achievement (with all other upstream latent constructs held constant). However, other statistical education researchers also have found this relationship lacking (Wise 1985; Wisenbaker et al. 1999; Wisenbaker et al. 2000). Instead of having the expected impact on Achievement, Value became a second outcome variable in the Pruned Model. Clearly, further investigation of the Value-Achievement relationship (or its lack) is needed.

Second, our results suggest a complex relationship between Difficulty and Value for engineering students. The direct effect from Difficulty to Value was large and negative. Among students who liked statistics equally, those who believed that the domain of statistics was easier valued it less. However, the indirect effect of Difficulty on Value (through Cognitive Competence to Affect and then to Value) was equally large and positive in direction. That is, engineering students who believed that the domain of statistics was easier reported higher self-concept in their abilities to do statistics which caused them to like statistics better and so value it more. The total impact, then, of Difficulty on Value was negligible. Obviously the relationship between Difficulty and Value is complex. This complexity was identified only because we explored direct and indirect, as well as total, effects.

Third, Cognitive Competence and Achievement correlated at almost a 0.5 level in the Baseline Measurement Model. Previous research suggests that this attitude component is important for successful course completion (Del Vecchio 1994). Yet its direct path was not statistically significant in the Saturated Model and so was eliminated in the Pruned Model. Its indirect path to Achievement through Affect was positive and small in size. This finding suggests higher self-concept about their statistical abilities encourages engineering students to like statistics more, which improves their achievement.

Fourth, six other direct effects suggested by expectancy-value (and other) theories were not statistically significant and so were eliminated to form the Pruned Model. These paths included those from Previous Success to three of the four attitude constructs (Difficulty, Affect, and Value), two paths from Difficulty (to Affect and to Achievement), and the path from Cognitive Competence to Value. Some of these constructs impacted others indirectly, but theory (and instructor beliefs) suggests direct impacts also.

Our results must be considered in light of the sample that provided these data. Undergraduate engineering students enter their post-secondary educations with strong math skills and generally positive attitudes toward math. They are required to increase their math skills through college-level math courses and the use of math in their engineering courses. Perhaps some of our unexpected findings were due to the characteristics of this sample.

However, many of our findings from the Pruned (and the Saturated) Models support theoretical and educational expectations. As expected, engineering students who reported more prior academic success also achieved more highly in their introductory statistics course and felt more confident in their statistics skills. Students who felt that the domain of statistics was easier to learn also expressed more self-confidence in their ability to learn statistics. Students who were more self-confident about their abilities in statistics also liked statistics better. Students who liked statistics more valued it more highly and achieved more.

The four attitude constructs were measured near the end of the introductory statistics and probability course. Although measured concurrently, expectancy-value models suggest, and so our models reflected, different developmental paths for these attitude components.

Our results are consistent with a model of statistics achievement in which attitudes toward statistics (at least those measured at the end of the statistics course) are important causes of statistics achievement for engineering students, although not as important as prior achievement. In the Pruned Model, the three attitude components of Affect, Cognitive Competence, and Difficulty together contributed about one-third of the explained variance in statistics achievement scores; Prior Success accounted directly for the remaining two-thirds. In the Saturated Model, the four attitude components were even more important, contributing 45% of the explained variance in Achievement.

In understanding the relationships among attitudes toward statistics and achievement, it is useful to think about attitudes as a second-order construct made up of several interrelated but separate components. In this study, we used the attitude components of Affect, Cognitive Competence, Value, and Difficulty but these may not be all of the important components.

A better understanding of the impact of the components of attitudes toward statistics on statistics achievement (and statistics course completion) for a variety of student groups can have many positive outcomes. Statistics teachers are more likely to take into account the impacts of attitudes on their students if a model can be found which sensibly links these constructs and empirically demonstrates their importance. With the use of a simple attitude instrument given within the first few weeks of class, professors acknowledge the importance of attitudes; they also may be able to identify students who may have difficulty and intervene before the students drop or fail the course.

There are differences among every student sample used in statistics education research. The impact of these differences on research results needs to be identified. Understanding these differences will help us build a more accurate model of the complex causal relationships among attitudes toward statistics and statistics learning. Research studies exploring other theoretically based structural models with different indicator variables as well as additional attitude components and other student samples are needed.

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Appendix: Mean, standard deviation, and correlation matrix for observed variables

	Mean	SD	affect1	affect2	cog1	cog2	value1	value2	value3	diff1	diff2	well	good	gpa	quiz pct	midpct
affect1	4.49	1.31	1.00													
affect2	5.06	1.08	0.71	1.00												
cog1	5.53	0.98	0.53	0.55	1.00											
cog2	5.44	1.10	0.66	0.71	0.63	1.00										
value1	5.09	1.07	0.36	0.44	0.26	0.31	1.00									
value2	5.20	1.25	0.35	0.43	0.13	0.30	0.70	1.00								
value3	5.10	1.38	0.41	0.44	0.22	0.31	0.70	0.81	1.00							
diff1	3.95	1.03	0.46	0.43	0.38	0.48	0.09	0.00	0.01	1.00						
diff2	4.21	1.07	0.47	0.43	0.34	0.50	0.11	0.04	-0.02	0.68	1.00					
well	6.28	1.06	0.07	-0.01	0.14	0.06	-0.03	-0.06	-0.03	0.01	0.11	1.00				
good	6.06	0.91	0.18	0.12	0.26	0.23	0.02	0.01	0.00	0.15	0.21	0.41	1.00			
gpa	3.22	0.46	0.20	0.18	0.17	0.15	0.07	0.07	0.08	0.09	0.08	0.27	0.39	1.00		
quizpct	83.48	10.69	0.44	0.36	0.27	0.35	0.14	0.13	0.16	0.23	0.23	0.20	0.22	0.60	1.00	
midpct	72.85	18.70	0.39	0.31	0.23	0.28	0.05	0.12	0.08	0.17	0.25	0.15	0.14	0.39	0.45	1.00
finalpct	63.35	15.87	0.35	0.24	0.21	0.27	0.05	0.04	0.07	0.15	0.26	0.22	0.26	0.52	0.59	0.31

Figure 1: Statistics Attitudes-Achievement Structural Model (standardized parameters)

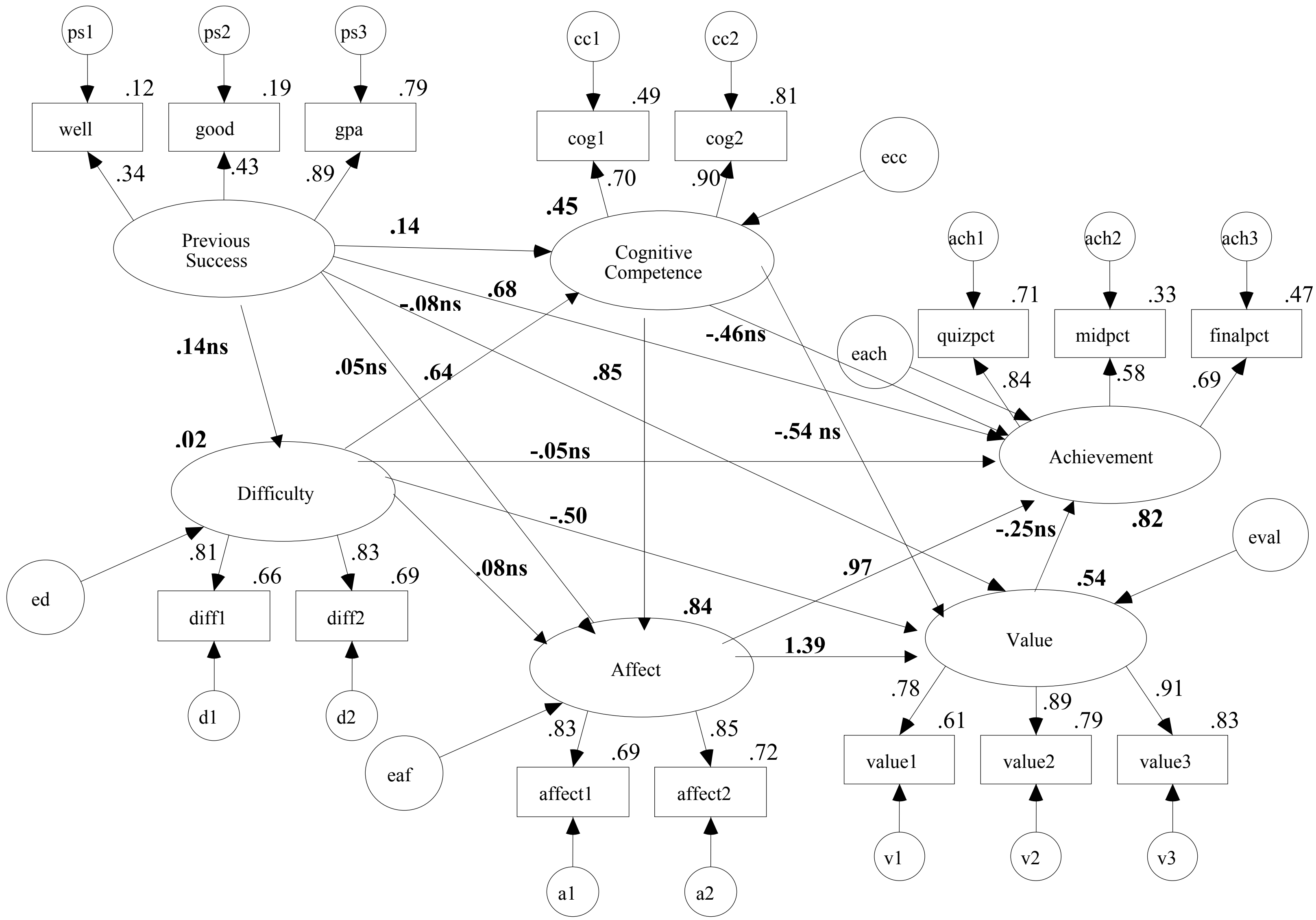

Figure 2: Final Baseline Measurement Model (standardized parameters)

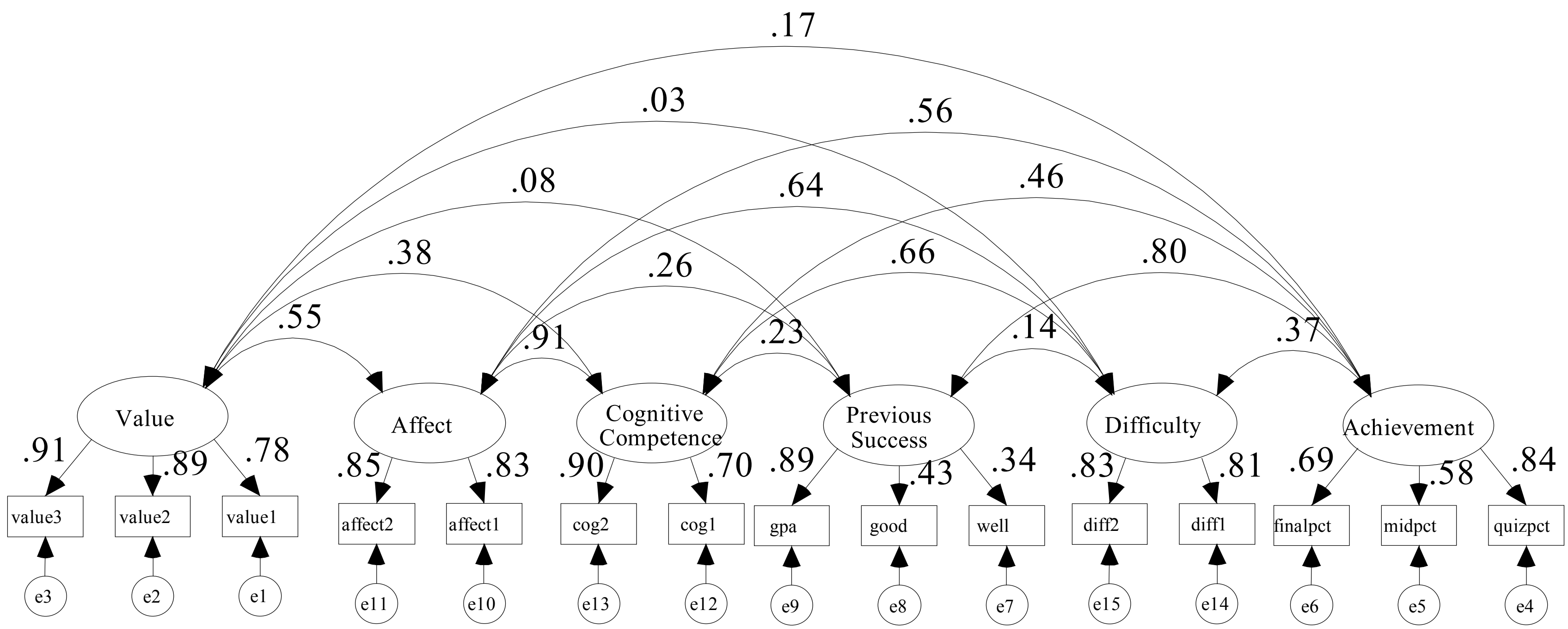

Figure 3: Pruned Statistics Attitudes-Achievement Structural Model (standardized parameters)