Temporal Cross-lagged Effects between Subjective Norms and Students' Attitudes Regarding the Use of Technology

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Abstract

The present study concentrated on the interplay of subjective norms and attitudes towards WebCT over time in a U.S. higher education setting. Panel data collected on three occasions over the course of a semester were investigated in a Web-enhanced hybrid undergraduate psychology course, using a crosslagged and autoregressive model. Results suggested: 1. the degree to which students report deferring to their professor's expectations and peer opinions (subjective norms) influences the degree to which they, on future occasions, report deferring to their professor's expectations and peer opinions; 2. students' attitudes towards using WebCT influence their attitudes assessed on immediately following occasions, but only those attitudes assessed immediately afterwards; 3. the degree to which students report deferring to professorial expectations and peer opinions (subjective norms) influences contemporaneously measured attitudes toward WebCT use; 4. student attitudes regarding WebCT use actually influence how students on a later occasion report their degree of deference to professorial expectations and peer opinions (subjective norms). Further research was suggested.

Keywords : *Crosslagged and autoregressive model; Subjective norms; Students' attitude; WebCT introduction*

Introduction

The success of computer training programs has been studied widely from the angle of system user characteristics, because such success may be determined not only by the features of the technology used but by the attitudes, perceptions and expectations that participants possess when either opportunities or demands to use technology arise. The Technology Acceptance Model (TAM), in particular, has been found to be a successful, yet parsimonious, representation of how perceptions and attitudes affect system use in a number of contexts. The model may be seen as a useful explanation of why people differ in terms of their success in using technology (Davis, 1989). Key features of this model include system user perceptions of a technology's usefulness, their perceptions of a technology's ease of use, and their attitudes toward the use of technology. The essential TAM proposes that these three factors impact both the frequency and duration of technology use in a given setting. Specifically, an end-user's perceptions of both the usefulness and ease of use of technology are predicted to affect his or her actual use, mediated by the system user's attitude (see Figure 1; Davis, 1993).

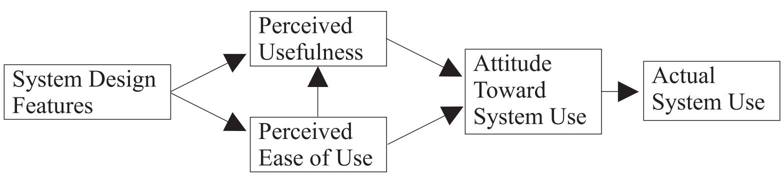


Figure 1

Literature Review

Researchers who have previously tested TAMs have exchanged system design features for other potentially relevant variables external to the other variable relationships (e.g, Legris, Ingham, & Collerette, 2002; Venkatech, 2000; Wiedenbeck & Davis, 1997). Recently, Pan, Sivo, and Brophy (2003), motivated by research findings concerning client side features, considered computer self-efficacy and subjective norms as potentially germane variables exogenous to the otherwise hypothesized TAM process. Pan, Sivo, and Brophy were particularly interested in the viability of such a model in the context of a semi-virtual classroom enhanced by WebCT instruction, a system previously investigated by Sanders and Morrison-Shetlar (2001). They focused their investigation on 217 students taking a web-enhanced undergraduate introductory psychology course.

Pan, Sivo, and Brophy added subjective norms to the TAM model, in part, because of the reasoning of Wolski and Jackson (1999). Wolski and Jackson argued that within educational institutions the model fails to capture all relevant aspects of technology acceptance, particularly the force that normative influences have. Peer pressure and faculty expectations play a role in student perceptions in a university environment. Venkatech and Davis (2000) studied the influence of perceived social norms within the context of the TAM model and found that perceived social norms (subjective norms), indeed, contributed to explaining variation in attitudes and behavior. Supporting this finding, Anandarajan, Igbaria, and Anakwe (2000) found social pressure to be a highly relevant component to include when attempting to understand microcomputer use. So, further consideration of this factor was reasonable in an educational environment, specifically a web enhanced psychology classroom. Pan, Sivo, and Brophy (2003) supplemented the TAM model further with an assessment of computer self-efficacy because Lee (2002) found it to be related to system user attitudes as well.

Relevance of the Study

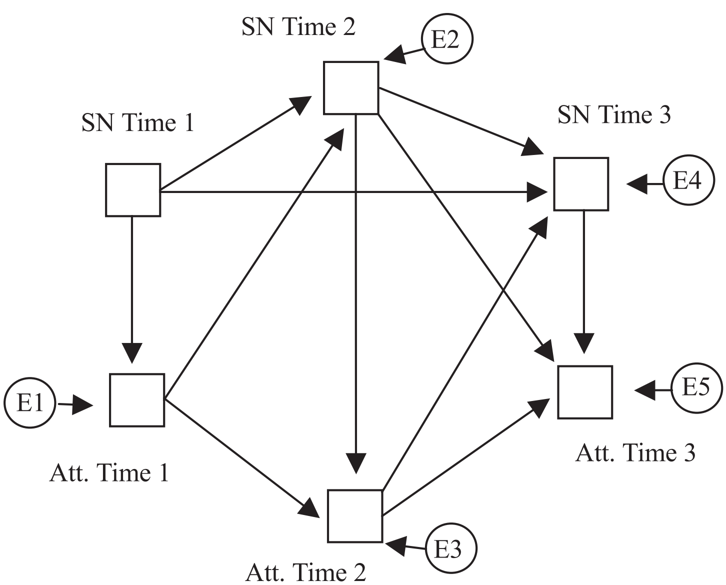
Oddly enough, Pan, Sivo, and Brophy (2003) found the TAM model, augmented by computer self-efficacy and subjective norms fit the data poorly in the U.S. higher education setting. Moreover, these findings were not due to the inclusion of subjective norms, but instead aspects of the standard hypothetic TAM failed to explain user attitudes and actual system use. In the end, social norms and attitudes towards system use alone were contributive to an understanding of actual system use, measured in terms of system use frequency. The relationship between subjective norms and attitudes toward system use was particularly notable and therefore merited further attention. To better understand the interplay of subjective norms and attitudes towards system use over time in this Web-enhanced hybrid undergraduate course, panel data collected on three occasions over the course of a semester were further investigated, using a crosslagged and autoregressive model. It was hypothesized that the same variable (both subjective norms and student attitudes regarding WebCT use) assessed over three time points would evidence an autoregressive pattern (Box & Jenkins, 1976).

Autoregressive (AR) models are constructed to allow the current value of a time series to be expressed as a function of previous values of the same time series:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + \varepsilon_t$$

where X_t denotes an observed score taken on some occasion (t) deviated from the original level X_0 of the series, ε denotes error associated with a given occasion (t), and ϕ denotes a correlation among temporally ordered scores at some lag (e.g., t–1 = a lag of 1, t–2 = a lag of 2). AR models have been increasingly used in the context of structural equation modeling in various contexts. With respect to longitudinal panel data, AR models for stationary processes have been discussed for both single indicator models (Sivo & Willson, 2000), multiple indicator models (Sivo, 2001), and single indicator growth curve models (Sivo, Fan, & Witta, in press).

In addition to specification of an autoregressive component in the model, a relationship between subjective norms and attitudes was hypothesized to be crosslagged (see Figure 2). If subjective norms is a precursor to attitudes toward using technology, and these effects persist over time, then it is reasonable to expect the ongoing influence of subjective norms on student attitudes over time to be ascertainable. Specifying crosslagged models for panel data is becoming more common as well in many contexts to depict cross variable interactions over time. Bentler, Newcomb, and Zimmerman (2002), for instance, fit such a model to adolescent data to explain cigarette use and drug use progression over time.



SN = Subjective Norm; Att. = System User Attitudes

Figure 2

Method

Participants

Two hundred and seventeen participants were recruited on a voluntary basis from an undergraduate psychology course, using WebCT as a Web-enhanced course (E-type). Female students accounted for almost 70% of the study participants, and roughly 70% were freshman. Approximately 70% were novice WebCT users. More than 90% have used the computer for more than four years. A breakdown of student participants by race/ethnicity is presented in Table 1.

Table 1

Race	Frequency	Cumulative Percent	Cumulative Frequency	Percent
Caucasians	154	70.97	154	70.97
African Americans	23	10.60	177	81.57
Hispanics	20	9.22	197	90.78
Asian Americans	17	7.83	214	98.62
Pacific Islanders	2	0.92	216	99.54
Native Americans	1	0.46	217	100.00

Data collection instrument

To measure subjective norms, a three-item scale that Wolski and Jackson (1999) developed was used. Furthermore, five items assessing system user attitudes toward technology were obtained from Davis (1989, 1993), Higher scores on the attitudinal scale suggested an overall more positive attitude. Results of reliability testing indicated that Alpha (α) value for each factor was greater than .7, which suggested that scales adapted were deemed reliable (see Table 2).

Table 2 Reliability Testing of the Scales

Factor #	# of items	Alpha
Attitude toward WebCT	5	.93
Subjective Norm	3	.75

Data collection and analysis procedures

Using Dreamweaver 4, Coldfusion, and MS Access, three online questionnaires were created and administered across three time occasions during the Fall 2002 semester. They were in the beginning, middle and end of the semester, respectively. Student informed consent was used. Two weeks before each administration, a friendly reminder (pre-notice) was sent via email to make sure sample subjects were informed of the incoming questionnaire. WebCT's Tip feature was also used for announcement-making. Additionally, teaching assistants of the course made an announcement in front of the class every time the survey was being administrated. Student participants were given a week to finish each questionnaire on a voluntary basis. Data sets from all time occasions were housed in a password protected server we were affiliated with.

We downloaded the data sets from the high secured server in MS Access. The data was imported to Word Pad as a text file for filtering. Then, the final copy of data was imported to SAS v8 for further analysis, using PROC CALIS, a structural equation modeling program. The results will be evaluated in terms of their propriety, fit and parsimony. The maximum likelihood estimator should converge for properly fitting models. Moreover, the estimated covariance matrix should be positive definite, with no negative eigenvalues and no collinearities. Also, the standard errors should be within proper bounds.

The following fit indices were examined: the Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Comparative Fit Index (CFI), Non-normed fit index (NNFI), Normed Fit Index (NFI), Standardized Root Mean Square Residual Estimate (SRMR), and the RMSEA. These indices were chosen because of their relative merits. The GFI, and AGFI are stand alone indices that have a long history in SEM research. The CFI, NNFI, and NFI are all Incremental Fit Indices that indicate how much the fit of a model improves upon the nested null model. These indices are more sensitive to misspecification between latent and manifest variables relationship misspecifications. The SRMR and RMSEA are more sensitive to latent-latent variable relationship misspecifications.

An assessment of adequate fit in structural equation modeling is not without standard cutoff criteria. In part, the cutoff criteria chosen are the result of Hu and Bentler's (1999) monte carlo simulation findings. The GFI, AGFI, CFI, NNFI, and NFI are all expected to exceed .95 if the model is to be deemed as fitting well. The SRMR and RMSEA are expected to attain values no higher than .05.

Results

The descriptive statistics obtained from the 217 undergraduate psychology students are presented in Table 3.

Table 3 Mean Scores and Standard Deviations of Variables

	Mean	Standard Deviation
Variables		
SN_T1	17.51152	2.84493
SN_T2	17.71889	2.71130
SN_T3	17.97696	3.01761
AT_T1	29.33641	5.50019
AT_T2	30.14286	4.93690
AT_T3	30.76037	4.87793

Note: SN_T1= Subjective Norms at Time 1, SN_T2= Subjective Norms at Time 2, SN_T3= Subjective Norms at Time 3, AT_T1= Attitude at Time 1, AT_T2= Attitude at Time 2, AT_T3= Attitude at Time 3.

Table 4 presents the covariance data analyzed in terms of the hypothesized model.

Table 4 Covariances of Subjective Norms and Attitudes toward WebCT

	SN_T1	SN_T2	SN_T3	AT_T1	AT_T2	AT_T3
SN_T1	8.093616	2.649086	3.067396	8.095643	5.463624	5.016662
SN_T2	2.649086	7.351169	4.072196	4.757040	5.494047	6.108252
SN_T3	3.067396	4.072196	9.105948	5.410564	5.697751	7.443527
AT_T1	8.095643	4.757040	5.410564	30.252048	17.729497	14.030060
AT_T2	5.463624	5.494047	5.697751	17.729497	24.373015	16.918650
AT_T3	5.016662	6.108252	7.443527	14.030060	16.918650	23.794162

Note: SN_T1= Subjective Norms at Time 1, SN_T2= Subjective Norms at Time 2, SN_T3= Subjective Norms at Time 3, AT_T1= Attitude at Time 1, AT_T2= Attitude at Time 2, AT_T3= Attitude at Time 3.

An evaluation of the model results suggests that the results were proper. The maximum likelihood procedure converged quickly to a solution with no evidenced collinearities or negative eigenvalues. Indeed, the predicted model matrix was positive definite, and the standard errors associated with the estimated parameters were within proper limits. The distribution of the errors was not wide and suggested nothing noteworthy.

The results obtained for the hypothesized crosslagged model fitted to the panel data suggest that the model fits extremely well, explaining the covariation in the data very well. The chi-square statistic was not statistically significant, suggesting that the model fitted well (see Table 5). The stand alone indices, including the Goodness of Fit index and its adjusted counterpart reached values in the neighborhood of .99, suggesting that the model does an excellent job of explaining the covariation in the data. Moreover, the incremental fit indices evaluated all exceeded .99, suggested that the model greatly improves upon the nested null model. These indices are very sensitive to manifest variable misspecification, so such results are reassuring. The SRMR and RMSEA, both reflecting whether the residuals, in sum, suggest poor fit, likewise suggested that the model fit very well, with values lower than the standard .05 cut-off.

Table 5 Model Fit Indices

Indices	Value
Chi-Square	1.6643
Chi-Square DF	4
Pr > Chi-Square	0.7972
Goodness of Fit Index (GFI)	0.9975
GFI Adjusted for Degrees of Freedom (AGFI)	0.9866
RMSEA Estimate	0.0000
Bentler's Comparative Fit Index	1.0000
Bentler & Bonett's (1980) Non-normed Index	1.0180
Bentler & Bonett's (1980) NFI	0.9967
Standardized Root Mean Residual (SRMR)	0.0312

The standard errors associated with the parameters estimated for the model suggest that all parameter estimates are tightly bounded. The associated t-values all exceed 2.00, further supporting the conclusion of their viability (see Table 6).

Table 6 Manifest Variable Equations with Estimates

SN_T2	=	0.0951*AT_T1	+ 0.2322*SN_T1	+ 1.0000 e1	
Std Err		0.0362 G2	0.0701 G1		
t Value		2.6249	3.3139		
SN_T3	=	0.4155*SN_T2	+ 0.1009*AT_T2	+ 0.1749*SN_T1	+ 1.0000 e2
Std Err		0.0709 B1	0.0395 B2	0.0665 G3	
t Value		5.8627	2.5556	2.6285	
AT_T1	=	1.0003*SN_T1	+ 1.0000 e3		
Std Err		0.1126 G4			
t Value		8.8854			
AT_T2	=	0.4098*SN_T2	+ 0.5216*AT_T1	+ 1.0000 e4	
Std Err		0.0950 B4	0.0468 B3		
t Value		4.3137	11.1379		
AT_T3	=	0.2041*SN_T2	+ 0.3755*SN_T3	+ 0.5604*AT_T2	+ 1.0000 e5
Std Err		0.0965 B6	0.0855 B7	0.0497 B5	
t Value		2.1156	4.3919	11.2767	

Inspection of the squared multiple correlations suggested that a substantial portion of each variable is explained, although only roughly 15% of the variation in subjective norms measured at the second time point is explained by subjective norms and student attitudes assessed on the first occasion (see Table 7). Nevertheless, 15% of the variation is sizeable enough to warrant inclusion of the paths between the Time One variables and Time Two subjective norms variable in the model.

Table 7 Squared Multiple Correlations

	Variable	Error Variance	Total Variance	R-Square
1	SN_T2	6.28367	7.35117	0.1452
2	SN_T3	6.30253	9.10047	0.3075
3	AT_T1	22.15438	30.25205	0.2677
4	AT_T2	12.87343	24.37302	0.4718
5	AT_T3	10.27166	23.78197	0.5681

Discussion

The purpose of this study was to follow up on Pan, Sivo, and Brophy (2003) finding that while the augmented TAM model fit poorly, a prominent relationship between subjective norms and student attitudes towards WebCT in a web enhanced classroom was evidenced. To better understand the dynamic between these two variables, this study investigated cross patterns of relationships over time. The hypothesized model was found to fit not only properly, but very well. The model suggests four conclusions, each of which comprises the model as specified. First, the degree to which students report deferring to their professor's expectations and peer opinions (subjective norms) influences the degree to which they, **on future occasions**, report deferring to their professor's expectations and peer opinions. Second, student attitudes towards using WebCT influence their attitudes assessed on immediately following occasions, but **only** those attitudes assessed immediately afterwards. The influence of their attitudes regarding WebCT use **on far later occasions** is not sustained. Instead, the influence of their initial attitudes about WebCT on attitudes assessed much later is mediated through their subsequently reported deference to professorial expectations and peer opinions (subjective norms). Thirdly, the degree to which students report deferring to professorial expectations and peer opinions (subjective norms) influences **contemporaneously measured** attitudes toward WebCT use. Lastly, student attitudes regarding WebCT use actually influence how students on a **later occasion** report their degree of deference to professorial expectations and peer opinions (subjective norms).

The results of this study suggest that when technology acceptance is to be investigated in educational contexts, it is quite meritorious for researchers to assess technology acceptance longitudinally, particularly if learners' attitudes toward a learning online technology are to be considered as a viable component in the TAM model. Moreover, it is advisable that subjective norms be included as a critical component in understanding system user attitudes. This study reaffirms the notion that modeling subjective norms is vital whenever attempting to understand end-user attitudes. Further evaluation of the utility of the TAM model in educational contexts for explaining the actual use of technology should be considered longitudinally, and specifically with the specification of crosslagged variable relations.

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