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Technology Acceptance Model of Online Learning Management Systems in Higher Education: A Meta-Analytic Structural Equation Model

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Abstract: The present meta-analysis employs meta-analytic structural equation modeling (MASEM) to quantitatively synthesize studies that investigates college students' acceptance of online learning managements systems. This study combined meta-analysis and path analysis to extend and refine the Technology Acceptance Model (TAM) within a higher education online learning environment context. Analyses of 13 studies representing 3407 undergraduate students from world-wide universities were conducted. The study investigated four path models (e.g., fixed-effects and random-effects) measuring different combinations of variables and formed conclusions about the relationships between the variables that were available. The model fit of each path model suggested mixed-results. Some models resulted in an acceptable fit, while others resulted in poor fit. Invariance tests resulted in statistically different findings across multiple parameter estimates, suggesting little to no replicability of findings across studies. Educational technology researchers should be cautious when forming conclusions about undergraduate online learning management systems based on the TAM.

Keywords: Meta-analysis; structural equation modeling; technology acceptance model; learning management systems.

1 Introduction

Practitioners need to gain an understanding of students' acceptance of the online learning environment.[24, 38] While instructors' preferences are often taken into consideration before implementing online learning; students' preferences are often explored only after adoption or when issues emerge during the course. Students' acceptance of the online learning environment is crucial to the success of online learning programs and for funds to be wisely invested. Before investing in online learning technologies, instructors understand whether the online learning environment will be accepted by the students involved. [2]

2 The Technology Acceptance Model

The Technology Acceptance Model[7] (TAM; c.f. Figure 1a) is one of many underlying theories used in technology adoption. The TAM is one of the most commonly used models to explain user's technology acceptance behavior. The TAM is rooted in Social Psychology Theory and the Theory of Reasoned Action. The core constructs in the original TAM include perceived Ease of Use (EU), Perceived Usefulness (PU), attitude (A) toward using, and actual system use (U). Over time, the model has been modified by adding constructs such as Behavioral Intention (BI) to use. Note, the TAM also specifies relationships between numerous endogenous variables (i.e., predictor variables) and other variables within the model.

Figure 1 depicts the evolution of the TAM between 1986 and 1996. At the TAM's core (Figure 1c), the TAM posits perceived ease of use and perceived usefulness of the technology will individually predict user's behavioral intention to use the technology. In other words, the easier the technology is to use or the more useful a particular technology is found to be, the more likely the user intends to use the technology again. The TAM (Figure 1c) also proposes that perceived usefulness mediates the relationship between perceived ease of use and behavioral intention to use the technology. This mediation effect may be observed when a technology is easy to use, but the technology is not useful to a person. If the technology is not perceived as useful, then it does not matter how easy the technology is to use; the end user will not continue to use the technology.

3 Literature Review

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To validate any version of the TAM, researchers must look at how the TAM functions with different technologies and different populations. One way explore this is to synthesize previous studies through meta-analysis. However, meta-analysts have faced numerous challenges in synthesizing the literature and in turn validating the TAM. One challenge meta-analysts face is the inability to conduct moderator analyses relating to a specific type of technology used. In the context of the TAM, a structural equation model, moderator analyses allow researchers to understand to what degree a model explains or predicts an outcome. This is important because the TAM may fit one technology well, while fit poorly with different technology. For example, Schepers and Wetzels[32] reviewed all empirical studies assessing the TAM. The authors had sufficient information to code for multiple types of technologies. However, there were not enough studies to conduct a moderator analysis based on a single technology. Instead, the meta-analysts aggregated all of the technologies into two categories (e.g., microcomputers and non-microcomputers). By narrowing these technologies into two groups, the study loses some of the information that could be observed by conducting a moderator analysis with more than two groups. To this end, model parsimony is favored when exploring numerous technologies.

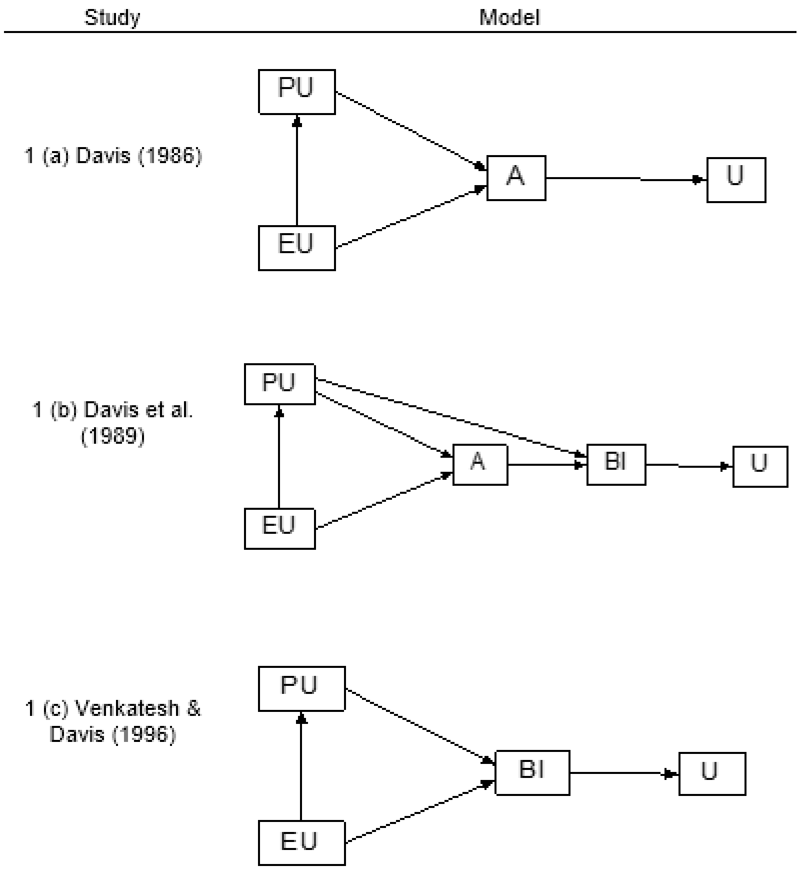


Figure 1: Evolution of Core Constructs In the Technology Acceptance Model.

Notes. PU = Perceived Usefullness; EU = Ease of Use; A = Attitude; BI – Behavioral Intention to Use the Technology; U = Actual Usage of the Technology.

Another challenge meta-analysts face is the inability to validate the TAM with a specific population. For example, King and He conducted a meta-analysis on the TAM using different users (e.g., students, professionals, and general users) and found differences between types of users.[13] More specifically, King and He concluded that, although students were similar to professionals, students were "not exactly like either of the other two groups" (p. 751) (i.e., professionals and general users). Although the researchers found that these groups were different, the results reported the results as if the groups were the same. Aforementioned with reviewing multiple technologies, parsimony within the study's sample is preferred.

Moreover, few meta-analysts of the TAM have conducted a meta-analysis of the TAM as a whole. Instead, previous meta-analysts have looked at each pairwise relationship within the model and formed conclusions regarding each relationship in the model. Tai, Zhang, Chang, Chen, and Chen[36] is unique in that the authors have evaluated the TAM as a whole by combining meta-analysis and structural equation modeling. However, Tai et al. only tested one version of the TAM.[36] It is unknown exactly why few researchers, with the exception of Tai et al., have attempted to validated the TAM as whole.[36] As discussed later, researchers may have had difficulty acquiring data to create a pooled covariance matrix. Unfortunately, primary studies of the TAM often only investigate the individual pairwise relationships within the TAM instead of investigating the TAM holistically, with a structural equation model mindset. As such, the meta-analyst must carefully pull effect sizes from each pairwise relationship that was investigated and create the covariance matrix for each study before the meta-analyst can begin to conduct the MASEM.

Previous studies have used meta-analytic techniques to validate the TAM; however, researchers failed to explore the TAM with a single type of technology or among a specific population using the TAM. [13,17] The results from prior meta-analyses suggest there is a lack of understanding of a specific population's ability to accept a specific type of technology.

4 Purpose

To date, researchers are unable to validate the TAM meta-analytically because previous analyses select broad populations (e.g., undergraduate students, professionals, and general users) and numerous technologies (e.g. learning management systems, email, word processors). Before investing in online learning technologies, practitioners should determine whether an online learning environment will be accepted by the students involved. In contrast to previous meta-analyses, the present meta-analysis isolated one population (e.g. undergraduate students) and one technology (e.g., learning management systems) to determine whether the core variables of the TAM explains undergraduates' acceptance of online learning management system by combining meta-analysis and structural equation modeling.

5 Methods

5.1 Search Procedures

First, articles were found using three academic databases: 1) ERIC database via EBSCO Host, 2) Educational Full Text via Wilson Web, and 3) Proquest Dissertations & Theses database via ProQuest. Similar thesaurus terms and keywords were used across all three databases. The database searched for the following words: "Technology Acceptance Model," AND "e-learning" OR "distance education" OR "online learning" AND "undergraduate" OR "college". The database search retrieved a total of 38 articles. After external duplicates were removed, 34 articles remained for screening. Table 1 presents the total number of articles retrieved from each database.

Second, articles were found while hand-searching articles from Ritter.[26] The hand-search retrieved 4 articles. Lastly, the reference section of the articles found in the database search and hand-search were searched. The reference list search retrieved 39 articles.

5.2 Screening

The screening process occurred in two phases: a primary and secondary (e.g. Moher, Liberati, Tetzlaff, Altman, & The PRISMA Group[20]), using an online reference management system, RefWorks. During the primary screening, each article's title and abstract was reviewed to determine if the article was written in English, was quantitative in nature, and tested the TAM. The articles which met the first screening's criteria progressed to the second phase. During the secondary screening, the entire article was reviewed to determine if the article included samples coming from an undergraduate student population, used the technology in an online learning context, reported adequate statistics to calculate covariances, measured all variables in the TAM, and measured variables at one time point. Interested readers may access the screened articles using the following permalink: http://goo.gl/5NYDKV.

Figure 2 presents the screening process, which includes the number of articles excluded and the reason for exclusion. The search process identified 77 studies with 34 found via databases and 43 found by hand searching or snowballing the reference sections of articles found in the database search. Three articles were excluded during the primary screening with one article excluded for being qualitative in nature and two articles did not test the Technology Acceptance Model. Sixty-one articles were excluded during the secondary screening. Six studies were excluded because those studies did not have samples consisting of undergraduate college students. Two articles were removed because those were not tested in an online learning context. Forty-nine studies were excluded because the researchers did not report sufficient statistics to calculate a covariances, which was needed to meta-analyze the studies. Two articles were excluded because they did not measure the variables represented in the TAM. Two studies were excluded because researchers used repeated measures design, which provided two different sets of data for the sample. These two studies were deemed more appropriate to compare results with rather than decide whether to synthesize pre-intervention or post-intervention results. After screening the 77 articles, a total of thirteen articles were included in current meta-analysis.

Most of the articles did not report sufficient statistics to synthesize results. Given that 49 articles would be excluded due to lack of statistics reported, two emails were sent to the authors whose articles did not contain statistics to compute a covariance. The first email requested missing information (e.g., means and SDs and/or correlations), and a second email followed two weeks later with a reminder of the initial request. Of the 49 articles with missing information, 13 authors responded, with one author providing the information requested. The most common response was to refer me to a co-author or suggest the data was lost.

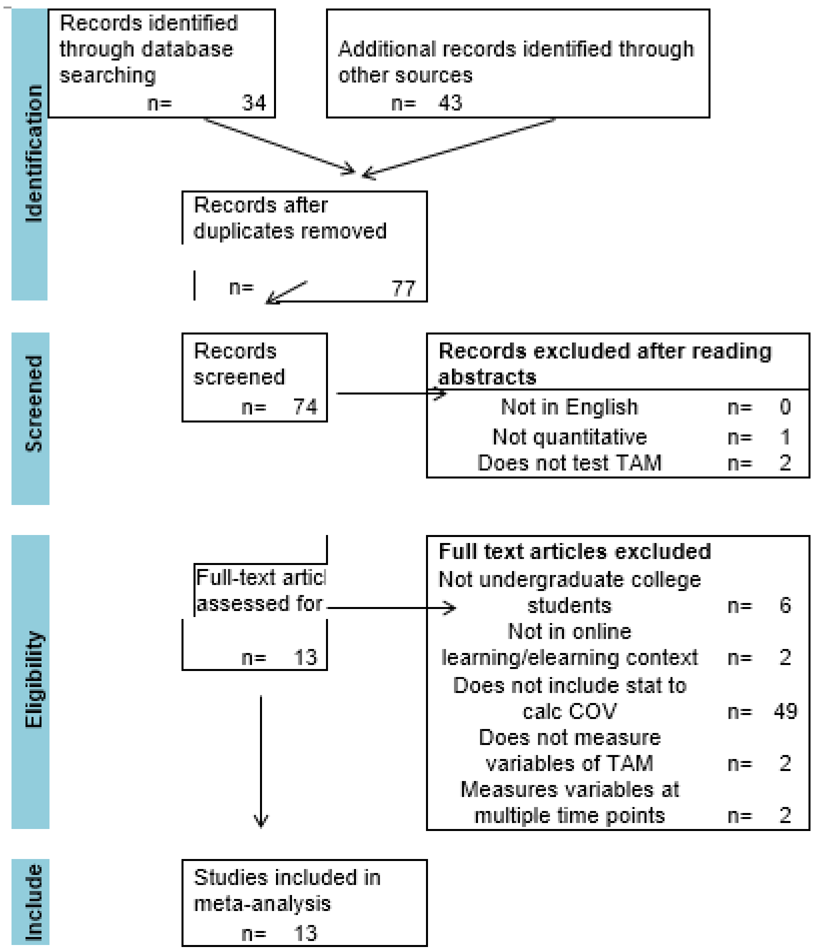


Figure 2: Article Screening Process.

All 13 articles meeting inclusion criteria were published in seven peer-reviewed journals. Most came from a single journal, *Computers & Education*. Table 2 presents the distribution of the articles according to journal.

Table 1 Articles Retrieved

Search	Database	Vendor	Number retrieved	External dups	New articles added
1	ERIC	EBSCO	16	0	16
	Education Full Text	EBSCO	19	4	15
	ProQuest Dissertations & Theses	ProQuest	3	0	3
2	Hand-searching	-	4	0	4
3	Reference lists	-	39	0	39
Total			81	4	77

Note. External dups = External duplicates between databases.

5.3 Coding Procedures

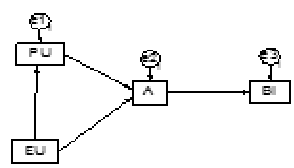
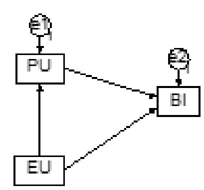
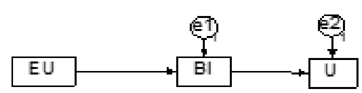
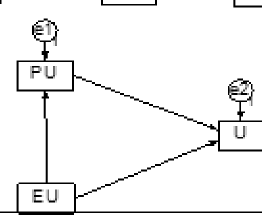
A coding scheme was created for the attributes of interest for the current study. All 13 articles were coded using an Excel spreadsheet. Given that the 13 studies measured different combinations of the variables in the TAM, the studies were grouped based on the common variables measured. Unfortunately, the studies had to be grouped by common variables measured because although MASEM can account for missing data, MASEM cannot account for missing variables. Table 3 presents the four groups tested. Each group included a different number of studies. As such, the covariance matrix used for each group of studies had a different number of variables (i.e., columns and rows in the covariance matrix) and different sample size.

Table 2: Journals Represented in Meta-Analysis

Rank	Journal	Count	%
1	*Computers & Education*	6	46.15
2	*Educational Technology & Society*	2	15.38
3	*International Review of Research in Open and Distance Learning*	1	7.69
4	*Turkish Online Journal of Educational Technology - TOJET*	1	7.69
5	*British Journal of Educational Technology*	1	7.69
6	*Behaviour & Information Technology*	1	7.69
7	*Journal of Educational Computing Research*	1	7.69

Note. n = 13.

Table 3: Groups of Studies Tested

Groups	Studies	Model
Group 1	Saadé & Galloway (2005) Saadé et al. (2007)	
Group 2	Almrashdah et al. (2010) Martins & Kellermanns (2004) Saadé & Bahli (2005) Saadé et al. (2007) Yi & Hwang (2003)	
Group 3	Liao & Lu (2008) Martins & Kellermanns (2004) Yi & Hwang (2003)	
Group 4	Brown (2002) Martins & Kellermanns (2004) Ramayah (2006) Yi & Hwang (2003)	

Once the studies were grouped, a meta-analysis within each group was conducted and then compared the studies within each group using multiple-group analysis. Given the number of parameters estimated in Groups 2 and 4, the SEM could not be identified. Hence, only the multiple-group analysis is reported for Groups 2 and 4. By grouping the studies based on the common variables measured, some of the 13 articles were not included in a given analysis.[8, 14, 28, 21] Furthermore, some studies were analyzed in more than one group.[18, 23, 31, 43]

5.4 Meta-analysis

The current meta-analysis used MASEM. MASEM combines meta-analysis and structural equation modeling by pooling covariance matrices and testing structural equation models using the pooled covariance matrix. The current study used Cheung and Chan's (2005) proposed two-stage structural equation modeling (TSSEM) approach to fit MASEM using covariance matrices.[6] The MASEM using the TSSEM approach was conducted using the metaSEM package version 0.8-4, the OpenMx package version 1.3.1-2301, and R version 2.15.3.[5]

5.5 Multiple group analysis

For the present study, a path analysis using maximum likelihood estimation was used to estimate the structural parameters of the variables measured in each of the studies. To test the invariance across studies, a multi-group analysis of structural invariance for each group of studies was conducted. The first step established a baseline model, labeled as Model 1 in each group. Secondly, a constrained model was established and labeled as Model 2 in each group. In the constrained model, each parameter was forced to be equal across all studies in the group. Thirdly, a chi-square difference test between Model 2 and Model 1 was conducted. If the chi-square difference test resulted in a non-statistically significant difference across the studies, it is concluded that the studies found statistically similar results. If the chi-square difference test resulted in a statistically significant difference across the studies, the specific path differences were located by
reviewing the critical ratios (e.g., z- statistics) of the parameter estimates in each study.

The AMOS software was utilized to conduct the multiple-group analysis. Multiple fit indices were reported and used to interpret model fit. While the chi-square test measures the model's ability to reproduce the sample covariance matrix; the chi-square test is sensitive to sample size and non-normality. Thus, several fit indices were considered to assess model fit, including root mean square error of approximation (RMSEA), root mean square residual (RMR), normed fit index, (NFI), goodness of fit index (GFI), and comparative fit index (CFI). RMSEA below .06 indicate a reasonable fit. An RMR of zero indicates a perfect fit; thus, the closer RMR is to zero, the better model fit. NFI, GFI and CFI values greater than 0.95 suggest reasonable model fit.[39]

6 Results

6.1 Meta-Analyses

Group 1

A fixed-effects MASEM combines two studies from Group 1. Figure 3 presents the model tested in the two studies.

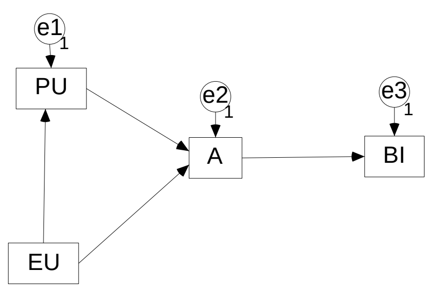


Figure 3 Group 1 Model

Notes. PU = Perceived Usefullness; EU = Ease of Use; A = Attitude; BI – Behavioral Intention to Use the Technology.

In Stage 1, homogeneity of the covariance matrices was met based on the goodness-of-fit indices: X^2 (df = 6, N = 490) = 12.78; p = .05, CFI = 0.99, TLI = 0.98, SRMR = 0.06, and RMSEA = 0.07. Given that the covariance matrices were homogeneous, the analysis continues to Stage 2 to fit structural model using RAM specification. In Stage 2, the fit indices of the structural model indicate good fit, X^2 (df = 2, N = 490) = 12.77; p = .0017, CFI = 0.99, TLI = 0.96, SRMR = 0.04, and RMSEA = 0.10. These indicators were consistent in indicating a generally acceptable fit of the hypothesized model to the data. Table 4 presents the standardized parameter estimates of the model.

Table 4: Group 1 Synthesis

		95% CI	
Parameter	Stand.	Lower	Upper
PU -> EU	0.51	0.44	0.57
PU -> A	0.52	0.45	0.60
EU -> A	0.16	0.08	0.24
A -> BI	0.61	0.55	0.67

Note. CI = confidence interval; Stand. = standardized estimate.

Group 3

A random-effects MASEM combines three studies from Group 3. Figure 4 presents the model tested in the three studies.

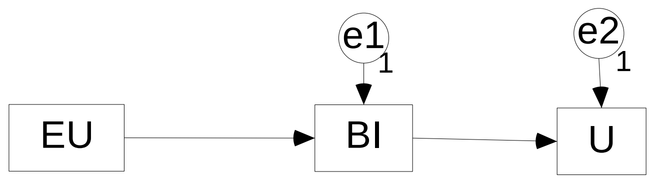


Figure 4: Group 3 Model

Notes. EU = Ease of Use; BI – Behavioral Intention to Use the Technology; U = Actual Usage of the Technology.

In Stage 1, homogeneity of the covariance matrices was not met based on the goodness-of-fit indices: X^2 (df = 6, N = 489) = 34.03; p = 0.98, CFI = 0.81, TLI = 0.71, SRMR = 0.16, and RMSEA = 0.17. Given that the covariance matrices were heterogeneous, a random-effects model is appropriate. In Stage 1, heterogeneity was confirmed Q (6) = 27.93, $p < .001$. The heterogeneity of EU, BI, and U were 97.30%, 96.64%, and 96.52%, respectively. In Stage 2, the fit indices on structural model indicates a perfect fit, X^2 (df = 1, N = 489) = 0.00, $p < .001$, CFI = 1.00, TLI = 1.00, SRMR = 0.00 and RMSEA = 0.00. Table 5 presents the standardized parameter estimates of the model.

Table 5: Group 3 Synthesis

		95% CI	
Parameter	Stand.	Lower	Upper
EU -> BI	0.55	0.38	0.68
BI -> U	0.36	0.23	0.50

Note. CI = confidence interval; Stand. = standardized estimate.

6.2 Multi-group Analyses

Group 1

Group 1 compared two studies. Figure 3 presents the model tested in the two studies. Table 6 presents the model fit statistics and the invariance test between the constrained and unconstrained model. Recall, the constrained model assumes the parameters from each study are equal to each other. The chi-square difference test was not statistically significant; thus, the parameter estimates across the two studies were statistically the similar or invariant. Table 7 presents the standardized and unstandardized parameter estimates.

Table 6: Model Fit Statistics and Invariance Analysis of Group 1

No.	Model	X^2	df	p-value	RMSEA	RMR	NFI	GFI	CFI	ΔX^2	Δ df	p-value
1	unconstrained model	16.5	4	.002	.080	.060	.972	.984	.979			
2	constrained model	23.2	8	.003	.062	.078	.961	.976	.974	6.7	4	.153

Note. n = 490.

Table 7: Parameter Estimates of Group 1

Study	EU -> PU		PU -> A		EU -> A		A -> BI	
	Stan.	Unst.	Stan.	Unst.	Stan.	Unst.	Stan.	Unst.
Saadé & Galloway (2005)[a]	0.47	0.41	0.47	0.46	0.03	0.02	0.55	0.63
Saadé et al. (2007)[b]	0.51	0.47	0.51	0.51	0.21	0.19	0.60	0.61

Note. [a]n_1 = 128. [b]n_2 = 36. Stan = Standardized estimate, Unst. = Unstandardized estimate.

Group 2

Group 2 compared five studies. Figure 5 presents the model tested in the five studies. Table 8 presents the model fit statistics and the invariance test between the constrained and unconstrained model. The chi-square difference test was statistically significant; thus, there is a lack of model invariance across the five studies in this group. In other words, the parameter estimates across the five studies were statistically different. Table 9 presents the standardized and unstandardized parameter estimates.

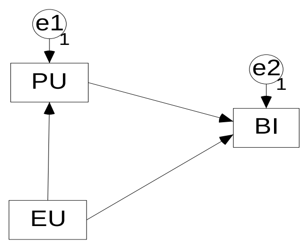


Figure 5: Group 2 Model.

Notes. PU = Perceived Usefullness; EU = Ease of Use; BI – Behavioral Intention to Use the Technology.

Table 8: Model Fit Statistics and Invariance Analysis of Group 2

No.	Model	X²	df	p-value	RMSEA	RMR	NFI	GFI	CFI	ΔX²	Δ df	p-value
1	unconstrained model	0.0	0	-	.256	0.000	1.000	1.000	1.000			
2	constrained model	143.4	12	p < .001	.094	.453	.883	.931	.892	143.4	12	p < 0.0001

Note. n = 1267.

Given that the five studies had different parameter estimates, a post-hoc analysis was conducted to determine which studies had similar or different parameter estimates. To identify differences, the critical ratios of the parameters estimates between each study were compared. Table 10 presents the critical ratios. A statistically significant critical ratio suggests that the parameter estimate in one study is statistically different than the parameter estimate in another study. For example, the critical ratio of EU -> PU in Almrashdah et al.[2] and Yi and Hwang[43] is z = -5.54 and is statistically significant at z = 1.96 (p = .05). Thus, the parameter estimates of the EU -> PU in Almrashdah et al.[2] and Yi and Hwang[43] were statistically different from one another. Conversely, the critical ratio of EU -> PU in Almrashdah et al. [2] and Martins and Kellermanns[18] is z = -1.328 and is not statistically significant at z = 1.96 (p = .05). Thus, the parameter estimates of EU -> PU in Almrashdah et al. [2] and Martins and Kellermanns[18] were similar to each other. The results of the post

hoc analysis across the five studies suggest that their parameter estimates may be different for EU -> PU and PU -> BI, but similar for EU -> BI. While the post hoc analysis provides potential insight to the nature of the differences in parameter estimates among the five studies, these results should be interpreted with caution. The post hoc analysis is exploratory in nature.

Group 3

Group 3 compared three studies. Figure 4 presents the model tested in the three studies. Table 11 presents the model fit statistics and the invariance test between the constrained and unconstrained model. The chi-square difference test was statistically significant; thus, there was a lack of model invariance across the three studies in this group. Table 12 presents the standardized and unstandardized parameter estimates.

Given that the three studies had different parameter estimates, a post-hoc analysis was conducted to determine which studies had similar or different parameter estimates. To identify differences, the critical ratios of the parameters estimates between each study were compared. Table 13 presents the critical ratios between the three studies. The results of the post hoc analysis across the three studies suggest that the parameter estimates were statistically different for both EU -> BI and BI -> U.

Table 9: Parameter Estimates of Group 2

	EU -> PU		PU -> BI		EU -> BI	
Study	Stan.	Unst.	Stan.	Unst.	Stan.	Unst.
Saadé & Bahli (2005)[a]	0.26	0.23	0.36	0.47	0.06	0.07
Saadé et al. (2007)[b]	0.51	0.47	0.42	0.42	0.05	0.05
Almrashdah et al. (2010)[c]	0.79	0.83	0.62	0.69	0.19	0.23
Martins & Kellermanns (2004)[d]	0.49	0.72	0.37	0.45	0.25	0.44
Yi & Hwang (2003)[e]	0.29	0.29	0.46	0.50	0.22	0.24

Note. [a]$n_1 = 128$. [b]$n_2 = 362$. [c]$n_3 = 425$. [d]$n_4 = 243$. [e]$n_5 = 109$. Stan. = Standardized estimate, Unst. = Unstandardized estimate.

Table 10: Critical Ratios of Parameter Estimates of Group 2

Study	Almrashdah et al. (2010)			Martins & Kellermann (2004)			Saadé & Bahli (2005)			Saadé et al. (2007)		
	EU - PU	PU - BI	EU - BI	EU - PU	PU - BI	EU - BI	EU - PU	PU - BI	EU - BI	EU - PU	PU - BI	EU - BI
Almrashdah et al. (2010)[a]												
Martins & Kellermann (2004)[b]	-1.328	-2.564*	1.748									
Saadé & Bahli (2005)[c]	-6.501*	-1.629	-1.222	-4.048*	0.153	-2.370*						
Saadé et al. (2007)[d]	-7.012*	-3.414*	-2.3*	-2.705*	-0.264	-3.244*	2.438*	-0.349	-0.197			
Yi & Hwang (2003)[e]	-5.54*	-1.761	0.123	-3.435*	.446	-1.427	0.461	0.203	1.154	-1.736	0.730	1.814

Note. [a]$n_1 = 425$. [b]$n_2 = 243$. [c]$n_3 = 102$. [d]$n_4 = 362$. [e]$n_5 = 109$. * |z-value| statistically significant at $z \geq 1.96$.

Table 11: Model Fit Statistics and Invariance Analysis of Group 3

No.	Model	X^2	df	p-value	RMSEA	RMR	NFI	GFI	CFI	ΔX^2	Δ df	p-value
1	unconstrained model	23.5	3	$p < .001$	.118	7.526	.848	.971	.859			
2	constrained model	38.7	7	$p < .001$	.097	21.762	.750	.952	.782	15.2	12	$p = 0.0043$

Note. n = 489.

Table 12: Parameter Estimates of Group 3

	EU -> BI		BI -> U	
Study	Stand.	Unstand.	Stand.	Unstand.
Martins & Kellermanns (2004)[a]	0.43	0.76	0.30	0.31
Yi & Hwang (2003)[b]	0.35	0.38	0.26	18.74
Liao & Lu (2008)[c]	0.47	0.47	0.17	0.33

Note. [a]$n_1 = 243$. [b]$n_2 = 109$. [c]$n_3 = 137$.

Table 13: Critical Ratios of Parameter Estimates of Group 3

Study	Liao & Lu (2008)		Martins & Kellermanns (2004)	
	EU -> BI	BI -> U	EU -> BI	BI -> U
Liao & Lu (2008)[a]				
Martins & Kellermanns (2004)[b]	2.330*	-0.114		
Yi & Hwang (2003)[c]	-0.643	2.752*	-2.649*	2.756*

Note. [a]$n_1 = 137$. [b]$n_2 = 243$. [c]$n_3 = 109$. * |z-value| statistically significant at $z \geq 1.96$.

Group 4

Group 4 compared four studies. Figure 6 presents the model tested in the four studies. Table 14 presents the model fit statistics and the invariance test between the constrained and unconstrained model. The chi-square difference test was statistically significant; thus, there was a lack of model invariance across the four studies in this group. Table 15 presents the standardized and unstandardized parameter estimates.

Table 14: *Model Fit Statistics and Invariance Analysis of Group 4*

No.	Model	X²	df	p-value	RMSEA	RMR	NFI	GFI	CFI	ΔX²	Δ df	p-value
1	unconstrained model	0	0	-	.213	0.000	1.000	1.000	1.000			
2	constrained model	37.9	9	p < .001	.068	14.509	.903	.965	.924	37.9	9	p < 0.0001

Note. n = 700.

Table 15: Parameter Estimates of Group 4

Study	EU -> PU		PU -> U		EU -> U	
	Stand.	Unstand.	Stand.	Unstand.	Stand.	Unstand.
Brown (2002)[a]	0.39	0.40	0.04	0.05	0.32	0.37
Martins & Kellermanns (2004)[b]	0.49	0.72	0.23	0.28	0.07	0.13
Ramayah (2006)[c]	0.55	0.46	0.32	0.41	0.45	0.48
Yi & Hwang (2003)[d]	0.29	0.29	-0.04	-3.16	0.24	19.15

Note. [a]$n_1 = 73$. [b]$n_2 = 243$. [c]$n_3 = 275$. [d]$n_4 = 109$.

Given that the four studies had different parameter estimates, a post-hoc analysis was conducted to determine which studies had different parameter estimates. To identify differences, the critical ratios of the parameters estimates between each study were compared. Table 16 presents the critical ratios. The results of the post hoc analysis across the four studies suggested that the parameter estimates were invariant for both EU -> PU, PU -> U, but non-invariant for the path, EU -> U.

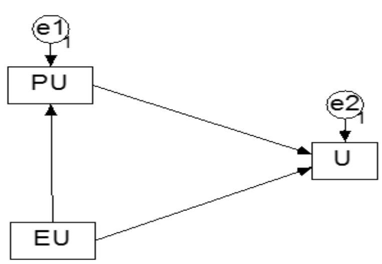


Figure 6: Group 4 Model

Table 16: Critical Ratios of Parameter Estimates of Group 4

Study	Brown (2002)			Martins & Kellermann (2004)			Ramayah (2006)		
	EU -> PU	PU -> U	EU -> U	EU -> PU	PU -> U	EU -> U	EU -> PU	PU -> U	EU -> U
Brown (2002)[a]									
Martins & Kellermanns (2004)[b]	-0.196	1.472	-1.283						
Ramayah (2006)[c]	0.454	2.410*	0.741	-2.795*	1.098	2.486*			
Yi & Hwang (2003)[d]	-0.774	-0.417	2.427*	-3.433*	-0.447	2.459*	-1.640	-0.463	2.414*

Note. [a] $n_1 = 73$. [b] $n_2 = 243$. [c] $n_3 = 275$. [d] $n_4 = 109$. * |z-value| statistically significant at $z \geq 1.96$.

7 Discussion

Technology adoption practices have received considerable attention in the last five years. With more funding offered for technology integration and implementation in a time when other funding is cut, universities are looking to online learning as a cost-effective option to deliver instruction. However, little is known about whether undergraduate learners will readily accept an online learning environment. In this technology age, many practitioners consider students proficient in technology. This assumption often stems from students' fluency with social media and entertainment media. However, researchers previously demonstrated that proficiently using technologies in personal and social settings does not necessarily transfer to the technology skills needed in an academic setting.[11, 16, 22, 37]

The purpose of the current study was to determine whether the TAM explains undergraduates' acceptance of online learning. In contrast to previous meta-analyses, which focused on a variety of populations and an array of technologies, the current study isolated both only one population and only one technology. Specifically, the present study investigated undergraduate students and online learning management systems. Furthermore, the present study utilized multiple group analysis to identify similarities and differences between studies. First, the relative fit of four groups of studies was tested using multiple group analysis. In Group 1, the studies were replicable, as assessed by the ΔX^2 test and fit indices seen in Table 6. In the remaining three groups, the studies had statistically different results (e.g., Tables 12, 15 and 18). Second, the critical ratios for each path in the proposed model were examined. The results suggest that the parameter estimates were different across certain paths and similar across other paths. This study suggests that the TAM is more context-sensitive than expected. These differences may be due to cultural differences[32,34] or gender differences[10] across studies. The following section expounds on the results from each group of studies.

Group 1 Studies

The results from the meta-analysis of Group 1 suggested that the fixed-effects model was an acceptable fit. The present study confirmed that perceived ease of use has a strong effect on perceived usefulness as demonstrated in previous studies. Both perceived usefulness and perceived ease of use influence individual attitudes. However, the relationship between perceived usefulness and attitude is stronger, $r = .52$, 95% CI [0.45, 0.60], than the relationship between perceived ease of use and attitude, $r = .16$, 95% CI [0.08, 0.24]. The influence of attitude to behavioral intention is also profound.

Likewise, the multiple group analysis echoed the findings of Saadé et al., suggesting that the parameter estimates were the similar across studies.[31] In fact, Group 1 was the only group of studies that were statistically similar. The results were reasonable given the studies' sample, learning management system, and instrumentation. The two studies were similar in that the two studies both draw on a sample from the same population. For example, Saadé and Galloway described their sample as students taking a "core management information systems course at Concordia University in Montreal, Canada" (p. 291).[30] Moreover, both studies used the same in-house-developed, learning management system, in which Saadé et al. referred to as a "multimedia learning system (MMLS)" (p. 175).[31] Additionally, Saadé et al. noted, that both studies used the same "methodology" and instruments (p. 178).[31] Given the similarities between the two studies, one would expect the results to be replicable, which the studies were.

This study offers further insight into the primary findings of Saadé et al.[31] While Saadé et al. used visual inspection of the parameter estimates across both studies, the present multiple group analysis utilized statistical-based invariance testing.[31] The multiple group analysis strengthens the previous findings of Saadé et al. and offers a clearer conclusion regarding the equality between each parameter estimate in the path model.[31] Moreover, the relationship between attitude and behavioral intention echoes the findings of Ursavaş.[40]

Group 2 Studies

The multiple group analysis results suggested that the parameter estimates were different across the five studies. First, the current study found the EU -> PU path was statistically different between 7 of the 10 pairs of studies. For example, Almrashdah et al.[2] and Saadé et al.[31] were statistically different from each other. Unlike Tai et. al.[36], the present results suggest mixed findings across the five studies regarding the relationship between ease of use and perceived ease of use. Second, the current study found the relationship between perceived usefulness and behavioral intention was relatively consistent across studies, with only 2 of the 10 pairs of studies diverging from each other. The results mirror Saadé et al.'s meta-analysis [31], which suggested a consistent and slight relationship between perceived usefulness and behavioral intention. Lastly, the relationship between ease of use and behavioral intention was statistically different between only 3 of the 10 pairs of studies, a result emulating King and He's findings.[13] Given the differences across studies, researchers should be cautious when forming conclusions regarding the relationships between the three variables: perceived usefulness, ease of use, and behavioral intention.

Group 3 Studies

The results from the meta-analysis suggest that the random-effects model represented in Group 3 was an acceptable fit. Despite the adequate model fit, researchers should be cautious when forming conclusions regarding the relationships between the three variables: ease of use, behavioral intention, and actual use, because the model tested only two relationships within the TAM. For example, the relationship between ease of use and behavioral intention was relatively strong, while the relationship between behavioral intention and use was moderate.

Furthermore, the multiple group analysis suggests that the parameter estimates were different across the four studies. First, the current study found the EU -> BI path was statistically different between 2 of the 3 pairs of studies. Second, the relationship between behavioral intention and actual use was statistically different across 2 of the 3 pairs of studies. The results suggest that the parameters estimates were different across studies, which also maintains the idea that findings were not replicable across studies.

Group 4 Studies

As seen in the multiple group analysis, results suggest that the parameter estimates were different across the four studies. First, the current study found the EU -> PU path was statistically different between only 2 of the 6 pairs of studies, suggesting Group 4 studies relatively reproduce a similar relationship between ease of use and perceived ease of use. Second, the relationship between perceived usefulness and actual use was relatively consistent across studies, because only 1 of the 6 pairs of studies were different from each other. Lastly, the relationship between ease of use and actual use was statistically different between 4 of the 6 pairs of studies. The results suggest mixed findings across the four studies regarding the relationship between ease of use and actual use, a finding which resonates with Ma and Liu.[17]

8 Limitations

Although primary studies have validated the TAM with undergraduate students in an online learning context, practitioners in the field should be cautious when making decisions about undergraduate online learning based on the TAM. Moreover, most of the prior meta-analyses have only looked at the bivariate relationships represented in the TAM, instead of the model as a whole, with one exception: Tai et al. meta-analytically tested the model as a whole using correlation matrices.[36] Tai et al.'s attempt was a progressive step and should be commended.[36] However, the study was limited by only using a pooled correlation matrix. The current study attempted to use a pooled covariance matrix, which provides more information for the path analysis. However, the present study faced many challenges in attempting to meta-analyze studies. Perhaps, Tai et al. encountered similar challenges, and therefore chose to utilize a more accessible correlation matrix to synthesize findings.[36]

This study faced many challenges in attempt to meta-analyze studies. First, the current study was limited by the range of variables included in past research, a limitation that Fried, Shirom, Gilboa, and Cooper also found in their meta-analysis using structural equation modeling.[9] Second, this meta-analysis was limited to the statistics provided by the authors. More specifically, the current study was limited by the range of variables included in past research. For example, studies that used the TAM tested different combinations of the variables within the multiple iterations of the TAM. By testing different combinations of variables, all 13 studies could not be synthesized together due to missing variables. Another challenge was the inadequate reporting of statistics to conduct the meta-analysis. Among the 77 articles identified, authors of 49 articles did not report the appropriate statistics to compute a covariance matrix. This denotes authors did not report either the means and/or standard deviations and/or correlations of the variables.

9 Conclusions and Implications

The advancement of online learning technologies has provided unmatched accessibility for colleges to meet the educational needs of students than ever before. As Bennett and Green noted, "There is little doubt that more and more college classes will be placed online in the future, and we are fast approaching the point when it will be the norm to have several courses online at the universities throughout the nation" (p. 495).[3] Although prophetic in its time, today this statement seems commonplace. While college administrators advocate for online courses, the current study suggests practitioners are making decisions based on non-replicable results. Essentially, this meta-analysis found that results from primary studies did not reproduce the same results when considering the model as a whole. As such, this study suggests that the TAM is not a good model to make decisions related to online learning management systems. As such, practitioners should not base learning management system adoptions based on studies that use the TAM.

The TAM is a popular model for explaining and predicting undergraduates' learning management system use. To date, researchers have conducted numerous studies on the TAM and obtained numerous confirmatory results through primary studies. Researchers have selected a variety of ways to validate or extend the TAM. For example, some researchers conducted replication studies, such as Adams, Nelson, and Todd[1], while other researchers rely on meta-analyses (e.g., Šumak, Heričko, & Pušnik[35]). Moreover, some researchers look to longitudinal studies (e.g., Venkatesh & Davis[42]), while other researchers relied on a series of single primary studies to validate or extend the TAM. The current study attempted to use meta-analytic structural equation modeling to validate or extend the TAM. Unfortunately, there were too many obstacles to definitively confirm any version of the TAM meta-analytically. Recall, that the studies used different versions of the TAM, preventing the current study to synthesize all 13 studies. As such, conclusions are formed based on smaller groups of three to five TAM studies. Although the findings of this study are useful, there are still questions about the TAM that cannot be answered meta-analytically.

However, researchers should heed the concerns expressed here regarding the application and accuracy of the model in an undergraduate online learning context. As demonstrated in the current study, some researchers may have formed erroneous conclusions regarding the relationships between the variables in the TAM. Moreover, the multiple group analysis suggests that the studies included here resulted in statistically different findings. Hence, the findings across studies were not replicable.

Consequently, researchers have spent over a decade modifying a theoretical model based on primary studies that has demonstrated little explanatory or predictive power. Hence, future research should be careful not to develop new models which would exploit the strengths of the TAM while ignoring the model's weaknesses. Future research should investigate stronger ways to proceed with model development within the TAM. This may be through investigating the construct validity of the TAM, testing and improving on the reliability and validity of the instruments used. In sum, practitioners should carefully consider students' preferences before investing in online learning technologies. However, practitioners should base their decisions on the findings from theoretical models validated in an online learning context.

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