

Learning Management System Adoption: A Theory of Planned Behavior Approach

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ABSTRACT

The growing popularity of online learning has put learning management systems (LMS) at the forefront of learning technologies. The adoption of LMS by students has therefore been a major driving force for online education. However, true adoption must transcend initial use for significant success. This study utilizes the theory of planned behavior (TPB) to gain new insights on students' short-term versus long-term adoption of LMS. Specifically, it examines the determinants of initial use and continuance use through the lens of the TPB. Results obtained from a sample of 248 undergraduate students suggest that difference in continuing use and initial use decision depends on differences in the influences of personal control perceptions about technology and subjective norms. Protagonists of online education will find these results interesting in that it provides insights for developing intervention strategies that can help in increasing online education adoption regardless of whether the focus is long-term or short-term.

KEYWORDS

Continuance Use, Innovation, Learning Management Systems, Learning Technologies, Online Learning, Technology Acceptance Model, Technology Adoption, Theory of Planned Behavior

INTRODUCTION

Learning Management Systems (LMS) have been widely used in higher education institutions in the United States and around the world; and this trend continues to rise (Lang, 2016). According to a 2014 *EDUCAUSE* Center for Analysis Research's report, 99% higher education institutions in the United States have an LMS in place, and 83% of students use some type of LMS. Among 17000 faculty members and 75000 students surveyed, majority of students and faculty members viewed LMS as an important tool for teaching and learning (Dahlstrom & Bichsel, 2014). Researchers have pointed to the critical role of LMS in student academic success (Paulsen, 2003; Browne, Jenkins, and Walker, 2006; Kumar & Sharma (2016). Despite the widespread use of LMS, not all university students are comfortable with their use, and others are unable to utilize them to the fullest ((Dahlstrom & Bichsel, 2014). While initial acceptance to LMS is a good step in the adoption process, an investigation into continuing acceptance is critical for long-term success of LMS (Joo, Kim, & Kim, 2016).

The use of LMS emerged in higher education in the 1990s and has quickly become an integral part of current teaching and learning experiences. The benefit of using LMS platforms such as *Blackboard*, *Moodle* and *Canvas* will not be maximized if students do not use them now, and continue to use them in the future (Alenzi, 2012; Lai, Wang, & Lei, 2012). In order to improve on LMS usage, researchers therefore, need to explore factors that give us a better understanding of the determinants of LMS among university students. Previous studies have highlighted some of these critical factors.

DOI: 10.4018/IJWLTT.2021010104

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For example, *usefulness*, *ease of use*, *perceived enjoyment*, *quality* and *attitudes* have been found to determine LMS adoptions among college students (Pituch & Lee, 2006; Lee, Cheung, & Chen, 2005; Saade, Nebebe, & Tan, 2007).

Many frameworks have been used by researchers to understand the spread and adoption of technologies such as these. Some examples include, the technology acceptance model, the theory of reasoned action, the theory of planned behavior, the expectation-confirmation theory among others. In this research we utilize the *theory of planned behavior* and the *expectation-confirmation theory* to examine this adoption concept. We do so for two major reasons: first, the theory of planned behavior has been acclaimed for its versatility in welcoming change interventions in behavioral research (Steinmetz, Knappstein, Ajzen, Schmidt, & Kabst, 2016). And since the adoption of LMS is behavioral in nature, and institutions need interventions that can encourage its use; a theory as the TPB seemed a great fit.

Second, many researchers have focused on the initial acceptance of the system and not really on the long-term continuance of use of the given system (Bhattacharjee, 2001). However, research shows that the real success of information systems (IS) lies in the continuing use of a system rather than in its initial acceptance, even though critical, is the actual measure of IS success. Hence, this research utilizes *continuance use intention*, instead of just *behavioral intention* to use a system and compares the two.

The current research therefore has as main focus to uncover the determinants of both *behavioral intention* to use (initial use intentions) and *continuance intention* to use (long-term use intentions). It also investigates into the difference between the two *use* outcomes based on the *attitude*, *subjective norms* and *perceived behavioral control*. The results of the study will benefit online learning champions seeking to increase adoption strategies.

In the following sections, we conduct a review of relevant literature, discuss how proposed model was developed, outline the methodology for the research, then analyze data, discuss results and offer a conclusion.

LITERATURE REVIEW

Many frameworks have been used in literature to explain the spread and adoption behaviors of information systems. Some of the popular theories include: the *theory of reasoned action*, the *theory of planned behavior*, the *technology acceptance model*, and the *theory of diffusion of innovations*.

The Theory of Reasoned Action (TRA)

Fishbein and Ajzen (1975) developed the theory of reasoned action based on value-expectancy theory. The value expectancy theory is based on the assumption that people change a behavior or adopt new behavior if they anticipate personal benefit from the outcome. Hence if the benefits outweighs the barriers they are more likely to indulge into behavioral change or adoption of a given behavior. Based on this notion, TRA assumes that behavior adoption or intervention is affected by intention towards the behavior and social influences towards it. Thus, TRA postulates that behavior is based on idea of intention; intention being the extent to which a person is ready to engage in a behavior (Fishbein, 1967; Ajzen & Fishbein, 1980). In general, people are likely to do something if they *plan* to do it than if they do not plan to do it. Therefore, as TRA suggests, intention is influenced by *attitudes*, *subjective norms*, and *volitional control*. Other researchers have shown that TRA adequately predicted the use of Massive Open Online Courses (MOOC) (Emad & Fajjida, (2019).

Based on the outcome, people therefore make series of beliefs towards a behavior, which in turn constitute an attitude toward that behavior (Ajzen, 2002). For example, if students believe that adoption of new LMS is beneficial, valuable, advantageous, or a good thing, then their attitude will be favorable and chances of them acting on the idea will be higher. Similarly, if students believe that adopting new LMS might not significantly impact their learning, is not useful to improve their academic performances and or improve their intellectual ability, their attitude toward the use of LMS

will be negative, and chances of their utilizing or adopting will be much lower. Thus, attitude plays important role in the TRA to impact intention.

Likewise, attitude can be influenced by subjective norms i.e. perceived social pressure whether to engage or adopt a certain behavior. Social pressure can arise from people who are close to the subject such as family, friends and relatives, whom the subject would like to please (Ajzen, 2002). Students are mostly surrounded by peers, teachers, and coaches who have important roles in their new behavior adoption decisions. Because of this, it's not uncommon that student behaviors are influenced by peers and teachers.

The TRA also postulates that adoptive behaviors need be under the control of the people who are trying to adopt the new behavior. This concept is known as *volitional control* (Ajzen, 1991). For example, if students want to adopt a new technology, it is possible that they make this decision entirely by themselves and not have to depend on other external factors. If the behavior in adoption is not under control, then chances of adoption are minimized significantly and adoption of the given behavior will be in question. Because the TRA excluded external influences which are clearly always present in real life, these external variables were later incorporated into the TRA to create a new theory called the Theory of Planned Behavior.

Theory of Planned Behavior (TPB)

The TPB is an extension of the TRA. In TPB, an additional construct, *perceived behavioral control* is added. Perceived behavioral control (PBC) is defined as an individual's perception of ease or difficulty of performing a behavior (Ajzen, 1991). The PBC construct additionally predicts intention. Hence, it makes general sense that the more favorable the attitude and subjective norm with respect to adopting a behavior, the greater perceived control and higher intention to perform or adopt a behavior. With these basic concepts, TPB has been widely and successfully used in understanding and predicting human behaviors (Fishbein & Ajzen, 2010). As of today, TPB has been used for many intervention programs such as in the field of nutrition (Kothe & Mullan, 2014); public health (Armitage, Harris, & Talibudeen, 2011); mental health (Skogstad, Deane, & Spicer, 2006), and many more. A recent meta-analysis by Steinmetz, Knappstein, Ajzen, Schmidt, and Kabst (2016) supports and validates previous findings on the predictive ability of TPB constructs on various behavior change interventions.

Technology Acceptance Model (TAM)

The TAM was theorized by Davis (1986) utilizing the basis of theory of reasoned action for the specific purpose of studying technology adoption and use of an information system. The core constructs of TAM include *perceived ease of use (PEOU)*, *perceived usefulness (PU)* and *behavioral intention (BI)* (Davis, 1989). According to TAM, PU is the subjective perception that a technology is useful to an individual adopting it and PEOU is the subjective perception that the technology is easy to use and it will enhance user's performance. TAM further claims that PU will be influenced by PEOU: i.e. when users perceive a technology as easy to use, they are likely to see the technology as useful one. Both of these constructs influence behavioral intention and are impacted by attitude toward using it. According Fishbein and Ajzen (1975), attitudes as an individual's positive or negative feeling towards a target behavior will impact behavioral intention. According to TAM, both PU and PEOU have impacts on user's attitude which ultimately drive adoption decisions.

Behavioral intention has been defined as the degree to which a person has formulated conscious plans to perform or not to perform a behavior (Davis, 1989). Attitude and PU directly influence behavioral intention. For example, if users develop positive attitudes about a technology, they find that technology useful and ultimately they develop positive intention to use that technology. Additionally, and based on TRA and TPB, an extension to TAM was later hypothesized with an additional construct called *subjective norms* (Venkatesh & David, 2000). Subjective norms have been defined as social influences originating a person's perception that most people who are important to them think they should or should not perform a particular behavior. Furthermore, subjective norms have been found

to affect intention (Taylor & Todd, 1995). The TAM is still a famous framework in the study and adoption in information technology, and has been widely used to predict the intention to use a given technology adoption (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008; Lee, Kozar & Larsen, 2003; Shaqrah, (2015).

The Theory of Diffusion of Innovation (DOI)

The diffusion of innovation theory originated from sociology and was first used to test innovative farming practices in the United States (Rogers, 2003). According to DOI theory, an innovation is something new or novel, whether a device, practice or idea. Diffusion refers to the process in which an innovation is disseminated and adopted in a society through the social system (Rogers, 2003). According to this theory, people go through several stages of decision making before they finally decide to adopt an innovation. First, is the *innovation-decision* process, which describes the awareness or initial knowledge of the existence of an innovation. Then comes *relative advantage* (is the degree to which an innovation is perceived as better than the idea it supersedes), *trialability* (innovation is tried before adopting), *complexity* (innovation is easy and simple to use), *compatibility* (innovation is compatible with existing values and needs of people, culture and society) and lastly, *observability* (innovation effects can be seen by others). According to this theory, for the innovation process to go through these steps, an appropriate communication channel is required over a period of time (Rogers, 2003). DOI theory is been used in the past by researchers to explain adoption behaviors such as hybrid corn seed by farmers (Valente & Rogers, 1995), physician's adoption of pharmaceutical products (Alkhateeb, Khanfar, & Loudon (2009), and forty years of practical application in the field of public health, (Haider & Kreps,(2010).

Each one of these theories are pivotal to understanding user decision-making on the adoption behaviors. In the context of this research, we are interested in how adoption decisions are made. Whether in its initial stages or repetitive decision-making, behavioral intention is front and center to adoption, and is the focus of our current research.

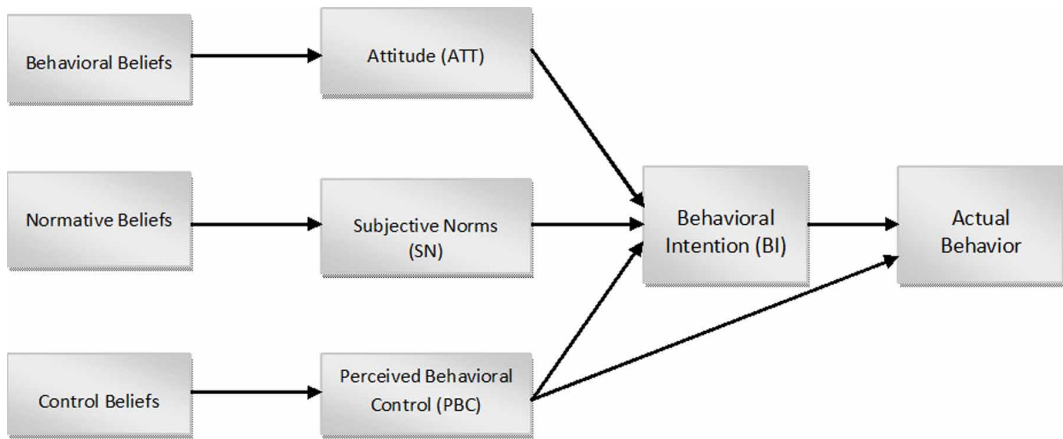
RESEARCH MODEL AND HYPOTHESES

This study utilizes the theory of planned behavior as a basis for understanding short-term and long-term adoption decision-making. The proposed research model is based on the conceptual model presented in Figure 1 below. As indicated in the literature review section, the TPB posits that human behaviors (actual behavior) can be predicted by their behavioral intention (BI) to perform the particular behavior of interest. It further posits that behavioral intention will be determined by attitude (ATT) towards the behavior, subjective norm (SN), and perceived behavioral control (PBC) (Ajzen 1991; Ajzen, 2012). Lastly, the theory postulates that attitudes, subjective norms and perceived behavioral control are each influenced by behavioral, normative and control beliefs of the persons who engage in these behaviors.

Behavioral Intention to Use, Continuance Intention to Use and Actual Behavior

Extant research has shown that intention is the best predictor of behaviors (Armitage & Conner, 2001; Winkelkemper, 2014), confirming earlier predictions Fishbein and Ajzen (1975) and Ajzen (1985). It can be said that as the behavioral intention to carry out a given behavior increases, the greater the tendency to carry the actual behavior. Since the target behavior in this research is the use of an online learning management system (LMS), the behavioral intention to use the system will positively affect the actual use of the LMS. Continuance intention (CINT) to use an information system is defined as the intention to use an information system beyond its primary acceptance. *Continuance* elaborates repeated use intention and has been found to positively affect actual use behavior (Bhattacharjee, 2001; Joo, Kim & Kim, 2016). Since this research emphasizes continuance intention, *continuance intention* was used in the proxy for *behavioral intention*.

Figure 1.



ATTITUDES TOWARDS AN LMS

According to the TPB, attitude towards a given behavior refers to perceived outcomes and attributes to the given behavior, and is dependent on salient beliefs to that behavior (Conner & Armitage, 1988). Attitudes are said to capture an individual's own evaluation of a target behavior, rather than the perceived social pressure to engage in the behavior—social norms. Hence, an individual's attitude towards the use of an LMS is likely going to influence their initial intention to use it and their subsequent intention to continue to use it, once they have experienced it.

It is therefore, hypothesized that:

H1A. Attitudes towards the use of an LMS will positively affect a student's initial intention to use the LMS.

H1B. Attitudes towards the use of an LMS will positively affect a student's continuing intention to use the LMS.

Subjective Norm

Subjective norm refers to the perceived social pressure to perform or not perform a behavior (Ajzen, 1991, p. 188). In an academic environment, students are constantly seeking the opinions of others on important behaviors that influence student life. The desire for students to continue to use a system based influence of teachers or peers is plausible. It is not unlikely that the opinion of referent others influence the way they view certain behaviors. Therefore, it can be said that to the extent referent others think positively or negatively of the LMS, it will influence the continuing use behavior of the LMS. Thus:

H2A. Subjective norms will positively affect a student's initial intention to use an LMS.

H2B. Subjective norms will positively affect a student's continuing intention to use the LMS.

Perceived Behavioral Control

The TPB depicts behavioral intentions as dependent perceived behavioral control, defined as the extent to which the performance of a behavior is easy or difficult (Ajzen, 1991). This construct is quite similar to self-efficacy as elucidated by Bandura (1980). According to the TPB, we are more likely to engage in behaviors in which we seem to have control over, rather than behaviors in which

we have little or no control over, holding intention constant. Based on the forgone, it is evident that as perceived behavioral control towards the use of LMS increases, so will the initial intention to use it as well as the intention to continue to its use past the initial use phase.

It can be hypothesized thus:

- H3A. Perceived behavioral control will positively affect a student's initial intention to use an LMS.
H3B. Perceived behavioral control will positively affect a student's continuing intention to use the LMS.

Actual Usage of Technology

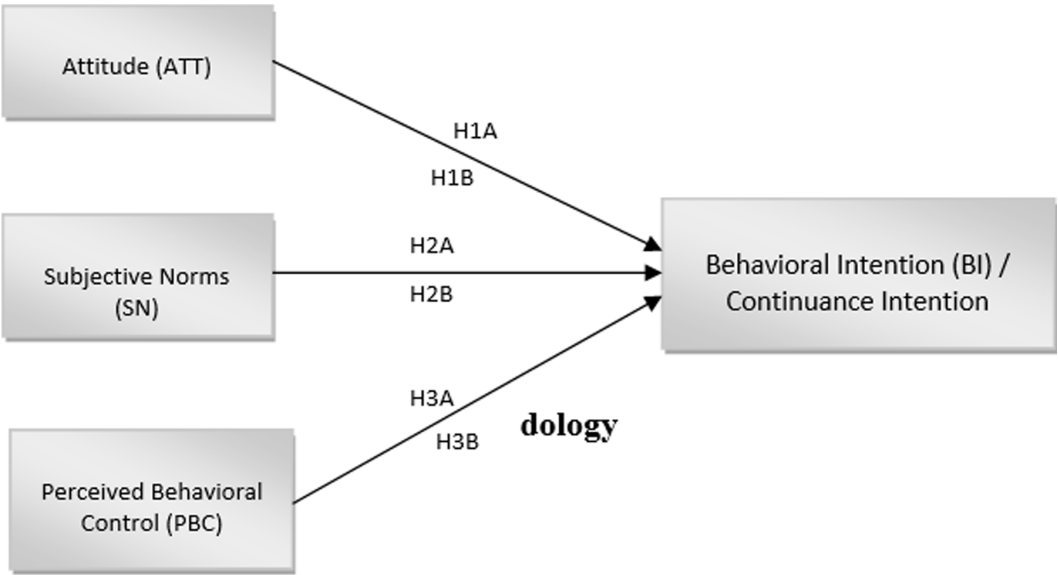
Previous research has established the importance of attitude, subjective norms and perceived behavioral control in determining behavioral intention as well as actual usage (Weigel, Hazen, Cegielski & Hall, 2014; Mathieson, 1991). Because intention is postulated to predict actual behavior, initial behavioral intention to use an LMS is and the behavioral intention to continue to use the LMS are both considered as proxies of actual behavior (Ajzen & Fishebein, 1991). A summary of research hypothesis is therefore summarized in Figure 2 below.

METHODOLOGY

Sample

The sample frame from which the sample was drawn comprised undergraduate students who were taking classes completely online. This means that these students, of necessity, had to depend on the use of the learning management system for their learning. The sample consisted of a group of undergraduate students using a learning management system for instruction in a medium sized Midwestern university in the United States of America. The sample of 248 undergraduate students from was drawn from two 100-level as well as a 400-level class health promotion and marketing classes. In total 76-male, 171-female, and 1-undisclosed gender of students participated. The number

Figure 2. Research hypotheses based on TPB



of survey questionnaires collected totaled 254 from a distributed total of 411 questionnaires, from all sections of the participating classes; yielding a 62% response rate. A summary of these descriptive parameters are included in Table 1 below.

Table 1. Descriptive statistics

Gender		Classes Participated	Number of Participants	Total Participants	Response Rate (%)
Male	76	Emergency Health Care	121	196	61.73
Female	171	Medical Terminology	130	167	77.84
Undeclared	1	Drug Use and Abuse	30	48	38.46
Total	248		281	411	

Measures

The survey items were implemented through a five-point Likert scale measure, and scales used were adopted from validated scales of the previous studies. More specifically for *attitude* we used Davis (1989); for *subjective norms* and *perceived behavioral control*, Taylor & Todd (1995); *behavioral intention*, Saade & Bahli (2005); and for *continuance intention*, we used Bhattacharjee (2001). The scales were adapted to fit the context of study. Consistent with social research, demographic variables were also collected especially gender.

Data Analysis Strategy

The data that were collected were analyzed using structural equation modeling technique. Based on the theoretical model above, two analytical models were designed: *Model A* and *Model B*. Model A, where *behavioral intention* to use was measured, and Model B where *continuance intention* to use was measured. More specifically, partial least squares structural equation modeling (PLS-SEM) conducted using smartPLS (v.3.2.8). The suitability of using PLS-SEM technique was based on recommendations of the general rules of thumb for this technique as specified by Hair, Hult, Ringle and Sarstedt (2017, p. 23).

Data Analysis and Results

First, the data were assessed for missing or incomplete values. Missing values were imputed using imputational methods recommended by Hair, Black, Babin and Handerson (2009; pp. 42-64). Where observations had missing data above 15%, the observation was dropped. Also, because indicator data that were missing were below 5%, mean value replacement strategy was used as recommended by Hair, Hult, Ringle and Sarstedt (2017, p. 57). The final sample therefore consisted of a total of 248 observations. This sample size was deemed appropriate considering the fact that conservative sample size estimate for the proposed model will require a 103 observations to achieve a statistical power of 80% at a 5% significance level for a minimum R-square of 0.10 (See Hair, Hult, Ringle & Sarstedt, 2017, p. 26).

Next, the proposed models (*Model A* and *Model B*) were run using the PLS-SEM technique. The measurement and structural model evaluations were also conducted. The constructs for both models were labeled as follows: Attitude (ATT) with indicators *ATT1*, *ATT2* and *ATT3*; Subjective Norm (SN) had indicators *SN1*, *SN2* *SN3*; Perceived Behavioral Control (PBC) with indicators *PBC1*, *PBC2*,

PBC3; Behavioral Intention with indicators as *BI1*, *BI2* and *BI3*; and Continuance Intention (CINT) with indicators *CINT1*, *CINT2*, *CINT3*, *CINT4*, *CINT5*.

Measurement Model Evaluation

Table 2 below shows a summary of *Model A* measurement results. The measurement model values allow us to assess the reliability and validity of both the indicators, constructs and model in general. More specifically, internal consistency was ascertained by examining the construct or composite reliability and Cronbach's alpha. As can be seen on Table 2, all the reliability test results were above the 0.70 threshold recommended by social research standards (Nunnally, 1978; Hair et al., 2009). Next, we evaluated the convergent and discriminant validity of the measurement model. These two measures specify whether the indicators for each construct are truly related to the construct while at the same time measuring whether the constructs are in fact different constructs. As Table 2 reveals, all indicators loaded on their constructs over the 0.70 threshold recommended except for *PBC1* which, was dropped from the analysis. The average variance extracted (AVE) was also above the 0.50 level recommended for social research; hence, establishing convergent validity. To ascertain discriminant validity, it is recommended that each indicator loads to its construct more than it does to any other construct in the model, and that the square root of the AVE exceed the correlation between constructs. In Table 2, the discriminant validity portion of the table indicates shows the square root of AVE in the diagonal position and the average correlations in the off-diagonal position. As is evident, the diagonal elements are higher than the off-diagonal ones; demonstrating discriminant validity of measurement model.

Table 2. Results summary of measurement model A evaluation

Latent Variable	Indicators	Convergent Validity		Internal Consistency Reliability		Discriminant Validity			
		Loadings	AVE	Composite Reliability	Cronbach's Alpha	ATT	SN	PBC	BI
		>0.70	>0.50	>0.70	>0.70				
ATT	ATT1	0.910	0.844	0.942	0.908	0.919			
	ATT2	0.937							
	ATT3	0.909							
SN	SN1	0.914	0.885	0.959	0.935	0.672	0.938		
	SN2	0.956							
	SN3	0.945							
PBC	PBC2	0.903	0.841	0.914	0.812	0.632	0.571	0.917	
	PBC3	0.931							
BI	BI1	0.934	0.880	0.957	0.932	0.596	0.480	0.542	0.941
	BI2	0.936							
	BI3	0.952							

Likewise, Table 3 also displays the results of the measurement model for *Model B*. When assessed for reliability and validity, the results were equally positive. For instance, all the composite reliability and Cronbach's alpha values were all above the 0.70 threshold level. Construct validity results showed that all items loaded to their corresponding construct beyond the 0.70 threshold level

Table 3. Results summary of measurement model B evaluation

Latent Variable	Indicators	Convergent Validity		Internal Consistency Reliability		Discriminant Validity			
		Loadings	AVE	Composite Reliability	Cronbach's Alpha	ATT	SN	PBC	CINT
		>0.70	>0.50	>0.70	>0.70				
ATT	ATT1	0.906	0.844	0.942	0.908	0.919			
	ATT2	0.937							
	ATT3	0.912							
SN	SN1	0.913	0.880	0.957	0.932	0.672	0.938		
	SN2	0.957							
	SN3	0.945							
PBC	PBC2	0.896	0.840	0.913	0.812	0.636	0.574	0.917	
	PBC3	0.937							
CINT	CINT1	0.856	0.712	0.925	0.899	0.706	0.625	0.554	0.844
	CINT2	0.838							
	CINT3	0.815							
	CINT4	0.862							
	CINT5	0.845							

and that the AVE numbers were significantly above the 0.50 recommended level. The constructs also discriminated against one another adequately. The square root of the AVE in the diagonal position for each construct was clearly higher than the correlation between the constructs; hence, establishing discriminant validity.

Structural Model Evaluation

The structural model results for *Model A* and *Model B* are illustrated in Figure 3 and Figure 4 below. The figures show all constructs, the corresponding path coefficients, as well as their p-values in parentheses. The criteria for assessing the structural model in the PLS-SEM is to evaluate the significance of the path coefficients, the level of the coefficient of determination (R-square) and the effect size (Hair, Hult, Ringle & Sarstedt, 2017). Path coefficients close to 1 demonstrate strong positive relationships; and are usually significant.

In *Model A*, the path coefficients to *behavioral intention* (BI) from attitude, subjective norms, and perceived behavioral control were 0.383 ($p < 0.05$), 0.077 ($p > 0.05$) and 0.256 ($p < 0.05$) respectively. All but the SN-BI path was not significant. The coefficient of determination (R-square) was 0.404. In *Model B*, the path coefficients leading to continuance intention were 0.469 ($p < 0.05$), 0.243 ($p < 0.05$) and 0.117 ($p > 0.05$) respectively. In this model, all but the PBC-CINT relations was not significant. The variance in continuance intention explained by predictor variables were 0.548.

DISCUSSION OF FINDINGS

The summary of the findings of this study are presented in Table 4 below. In *Model A*, the overall variance in behavioral intention to use a learning management system as explained by the independent variables (attitude, subjective norms and perceived behavioral control) was 40.4%. It is noteworthy

Figure 3. Structural Evaluation of Model A

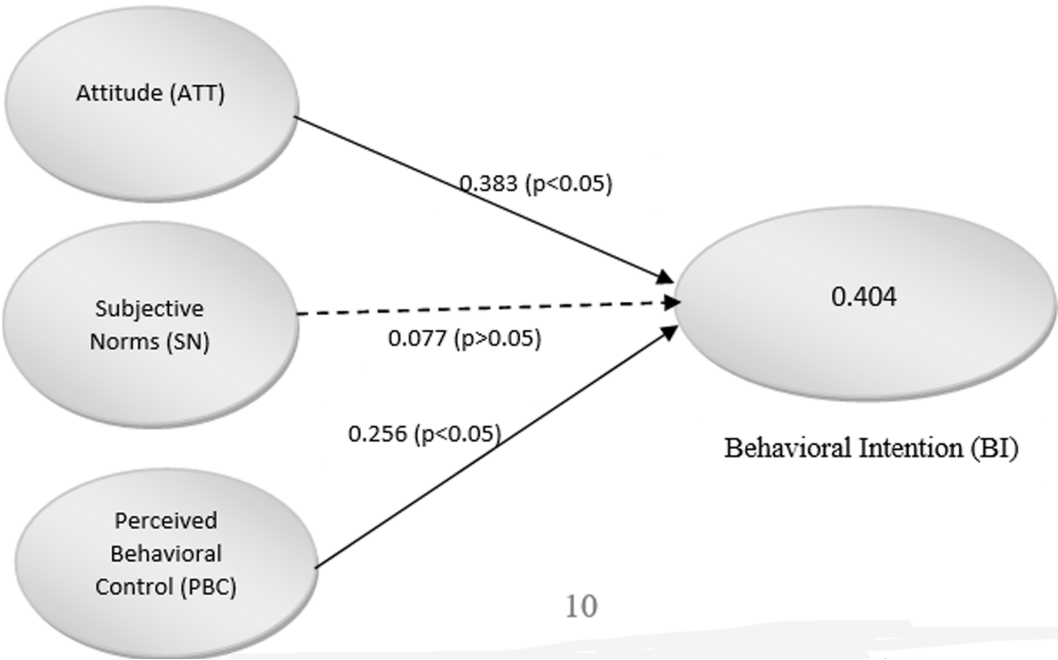


Figure 4. Structural Evaluation of Model B

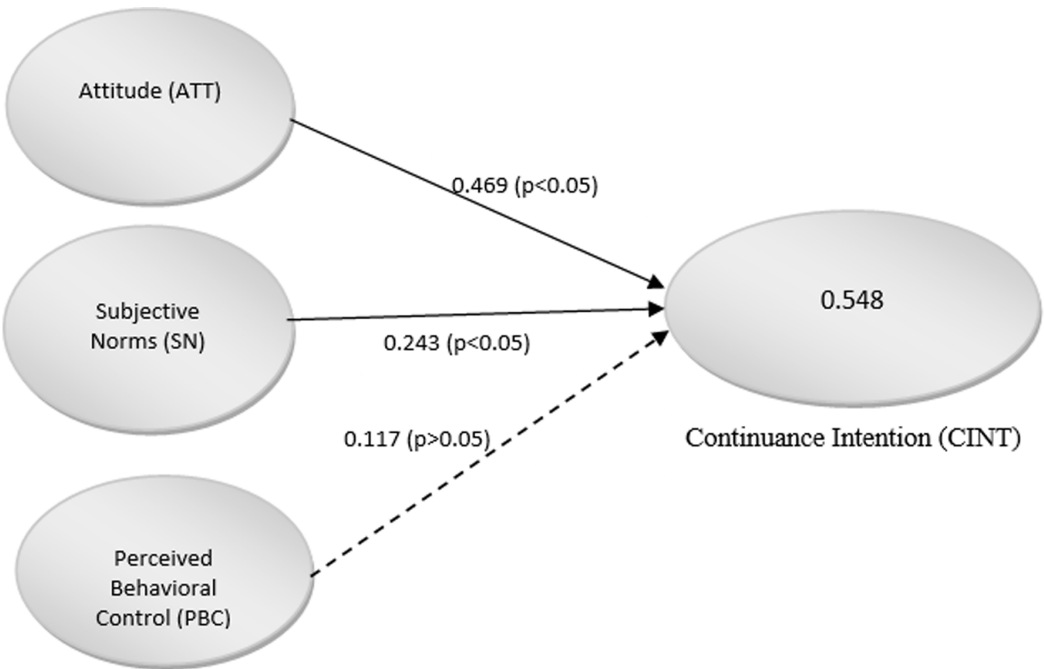


Table 4. Summary of hypotheses testing results

Hypothesis	Relationship	Proposed relationship	Result
H1A	ATT-BI	Positive	Supported
H1B	ATT-CINT	Positive	Supported
H2A	SN-BI	Positive	Not Supported
H2B	SN-CINT	Positive	Supported
H3A	PBC-BI	Positive	Supported
H3B	PBC-CINT	Positive	Not Supported

that the relationship between subjective norms and behavioral intention to use a learning management system (LMS) was not significant. Because behavioral intention to use the LMS is the same as the initial use of the system; these findings seem to suggest that when the concern of a student is initial adoption, the most critical predictors are attitude towards the system and perceived behavioral control. In other words, the more students have a positive attitude towards system use (attitude) and feel confident that they have control over the system (perceived behavioral control), the more likely they are to adopt the system for initial use.

On the other hand, *Model B* shows that the total variance in *continuance intention* to use an LMS as explained by *attitude* towards LMS, *subjective norms* and *perceived behavioral control* was 54.8%. However, the relationship between *perceived behavioral control* and *continuance intention* was not significant. This seems to suggest that the when the goal of the use of system is long term and repeated in nature, the most critical factors are *attitude* towards the learning management system and *subjective norms* about system rather than *perceived behavioral control* over the technology.

Looking at the two models together, we see that the total variance in *continuance intention* to use an LMS was greater than the variance in *behavioral intention* to use the system. This suggests that attitude, subjective norms and perceived behavioral control are stronger predictors of continuance intention than just initial intention. Another observation from the results is that when students are focused on initial or first time usage of a system, they lean more on the personal belief in themselves to handle the technology rather than on referent others. On the contrary, when it comes to continuance intention, the influence of referent others in the process seemed to be more important than just their personal control beliefs.

The results of this study revealed that the relationships within the *theory of planned behavior* constructs were generally validated at 95% confidence level. Additionally, there seemed to be a major difference between initial intention and continuance intention determinants. While personal control seemed to be necessary for initial technology acceptance, the perception of relevant others seemed to be important in determining *continuance intention*.

CONCLUSION AND IMPLICATIONS

The purpose of this study was to examine the adoption of learning management systems through the lens of a well-known framework of the theory of planned behavior. Specifically, we studied the effects of *attitude* towards LMS, *subjective norms* and *perceived behavioral control* on *use intention* behaviors. Instead of just observing *initial use* intention behaviors alone, we also tested the independent constructs against *continuance intention* and compared the two outcomes. Lastly, we wanted to know the salient determinants of short-term versus long-term use. The results of this study will help education professionals and researchers to consider the nature of intervention strategies that can be used to foster online education and learning.

The findings of this study lead to three major conclusions. First, the variance in *continuance intention* as explained by the predictor variables (i.e. *attitude*, *subjective norm* and *perceived behavioral control*) was greater than the variance in initial *behavioral intention* explained by same variables. More specifically, the predictor variables accounted for 54.8% of variance in *continuance intention* to use compared to 40.4% in initial *behavioral intention* to use LMS (see Figure 3 and Figure 4). These results seem to suggest that there exist a significantly stronger relationship *continuance intention* and the theory of planned behavior predictor variables than with just initial *behavioral intention*. *Continuance intention*, therefore is a stronger driver of adoption in the long term than just initial *behavioral intention* to use an LMS.

Second, the findings indicate that *subjective norms* were not significant in determining *behavioral intention* to use but were significant in determining *continuance intention*. This result seems to suggest that when the user of an LMS's intention is to continue to use the information technology, the opinion of significant others were salient in their decision making. However, when the usage was more short term oriented, users tend to rely on their perception of personal aptitude such as *behavioral control*.

Third, perceived behavioral control was not significant in determining *continuance intention*, but was very key in determining *behavioral intention* to use an LMS. This result seems to suggest that if the goal for an information system is long term continuance use, perception of personal aptitude and control is not nearly as important about the perception of relevant others.

The last two findings both point to two important one important conclusion. When focusing on long term adoption, while perceptions of individual control may be important, the perception of relevant others is even more crucial. On the converse, when the focus is short term, an individual's perception of control over usage behaviors are key to adoption than the consideration of just what relevant others think. Online learning promoters need to have the end game in mind when it comes to adoption of learning management systems. For instance, if the goal is to get a number of students take an online test; the strategy will be to be to use tap into or build their personal comfort level with the technology, or using their comfort levels with similar technology they have used to spur future use. However, if the end goal is, for instance, to earn a degree online, then the inclusion of relevant others, such as past students who had success in the past using the technology, would be important to highlight. Persuasive strategies must therefore be built with overall end-goal in mind.

Nevertheless, regardless whether the goal is short-term or long-term, if the adoption of online learning is to be encouraged and sustained, persuasive strategies that focus on the building personal aptitude perceptions as well as relevant others perception must be encouraged at the same time. For instance, while promoting an online program to potential learners, it would be important to showcase student users who have successfully used the system to get their training and degrees. This way, newer students are influenced by the benefit they stand to gain, and be motivated to adopt the system. Also, personal control perceptions should also be leveraged. For example: If online learning is being marketed to new students, a fun, interactive technology exercise can be given to them. After they must have completed this exercise; they are assured that if they could do the exercise on their own; they could do exactly what is required in the course or program, from a technology standpoint. These two approaches are likely to drive adoption quicker and faster since they act as intrinsic and extrinsic forces in boosting adoption.

The end-goal of technology implementation has always been its adoption by its intended users to improve performance and job outcomes. Improved performance and better outcomes means that revenues can be increased, costs can be cut, and profits can be raised. The overall findings of this research show that long term adoption of learning technologies lie in the perceptions of attitudes, control, and social pressure. The more strategies we formulate to improve perceptual attitudes, control and positive social pressure, the more likely we are to mitigate user resistance, spur adoption and ultimately improve outcomes.

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APPENDIX

Table 5. Questionnaire items

	Attitude (ATT)
ATT1	Using the LMS is a good idea
ATT2	I like using the LMS
ATT3	It is desirable to use the LMS
	Subjective norm (SN)
SN1	People important to me support my use of the LMS
SN2	People who influence me think that I should use the LMS
SN3	People whose opinions I value prefer that I should use the LMS
	Perceived behavioral control (PBC)
PBC1	Using the LMS system was entirely within my control
PBC2	I had the resources, knowledge, and ability to use the LMS
PBC3	I would be able to use the LMS system well for learning process
	Behavioral intention to use the system (BI)
BI1	I intend to use the LMS system in the future
BI2	I predict I would use the LMS system in the future
BI3	I plan to use the LMS system in the future
	Continuance Intention / Intention to Use (CINT)
CINT1	I will use the LMS system on a regular basis in the future
CINT2	I will frequently use the LMS system in the future
CINT3	I will strongly recommend that others use the LMS system
CINT4	I intend to take more courses using LMS system in the future
CINT4	I intend to show others this LMS system

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