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ORIGINAL ARTICLE

Empirical investigation of e-learning acceptance and assimilation: A structural equation model

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Abstract E-learning has become progressively more vital for academia and corporate training and has potentially become one of the most significant developments and applications in Information Technologies (ITs). This study used a quantitative approach seeking a causative explanation of the decision behavior of individuals toward the acceptance and assimilation of e-learning in academic settings. A survey of 286 participants (students) was conducted to collect the research data. Our study framework was based on the third version of the Technology Acceptance Model (i.e., TAM3) and the data were analyzed using structural equation modeling in order to determine the factors that influence the learners' intention to use e-learning. Results show the predicting (promoting/inhibiting) factors of e-learning technology acceptance, while also examining some related post-implementation interventions expected to contribute to the acceptance and assimilation of e-learning systems. Our results also indicate that TAM3 holds well in the Arabian culture and also outline valuable outcomes such as: managerial interventions and controls for better organizational e-learning management that can lead to greater acceptance and effective utilization. Hopefully, this study provides a roadmap to more understanding of the success factors

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and post-implementation interventions contributing to the acceptance and assimilation of e-learning systems in developing countries.

1. Introduction

The Internet and networks, as the backbone for modern communications, transformed our world into ubiquitous connectivity; that is, anytime, anywhere, access is always available to the digital network and digital services. The evolution (and revolution) in information and communications technologies (ICT), that recently fueled remarkable economic and social changes, will only pick up the pace as we apply managerial interventions and controls for better ICT acceptance and assimilation.

The Communications and Information Technology Commission (CITC) in Saudi Arabia has launched a longitudinal study which asserts that Internet penetration is relatively high among educational institutions, as 75% of them are being connected to the internet [16]. However, a striking finding of the study, declares that only 39% of university/college students are able to access the Internet by 2007 and that e-learning is also not very popular among the educational institutions in Saudi Arabia.

Technology-assisted learning via ICT (or e-learning) has become progressively more vital for academia and corporate training. Furthermore, e-learning has potentially become one of the most significant developments in ICTs [46]. Motivated by such compelling advantages as: geographical reach, learner control (in terms of flexibility and convenience), and cost effectiveness in course delivery and management, educational institutions and professional organizations are embracing e-learning by implementing an expanding array of technology-enabled platforms [27].

Recently, Saudi Arabia has called for a national plan to adopt IT spanning the country. The plan strongly recommends the implementation of e-learning and distance learning, and their prospective applications, in higher education. In a major transformation of conventional education, the Saudi Ministry of Higher Education has recently launched the National Centre of E-learning & Distance Learning, set up a repository to organize the change, and prepare e-learning materials to help universities adopt the system and transform to a scheme of e-learning quickly [39].

Technology Acceptance Model (TAM3) by Venkatesh and Bala [44] provides valuable rational explanations into how and why individuals make a decision about the adoption and use of ITs, particularly the work on the determinants of perceived usefulness and perceived ease of use. Moreover, TAM3 enlightens managers to make informed decisions about interventions that can be in charge of greater acceptance and effective utilization of ITs. This study draws heavily on the seminal work of Venkatesh and Bala [44] and Baker et al. [9] due to their interrelated nature dealing with IT acceptance and adoption testing as a common thematic issue. More specifically, Venkatesh and Bala [44] provide TAM3 as a theoretical base model while Baker et al. [9] provide the quasi replication and testing approach of a theoretical model in a different culture.

This study sets out an empirical research for investigating e-learning acceptance and assimilation in Saudi Arabia as having a unique culture that is different from the Western culture where TAM originated. The fundamental contribution of this study is to exploit TAM3 to predict technology acceptance of e-learning in Saudi Arabia as a developing country, in addition to inquiring for some related post-implementation interventions that might contribute to the acceptance and assimilation of e-learning systems in developing countries. The specific objectives of this study are: (i) to develop a customized Technology Acceptance Model using TAM3 for the determinants of the acceptance and assimilation of e-learning; (ii) to employ survey research to test the customized e-learning model per se; and (iii) to outline outcomes of the study, such as, the antecedents of e-learning technology acceptance and managerial interventions and control for better organizational e-learning management. It is hoped that this project provides a roadmap to a better understanding of the success factors and post-implementation interventions contributing to the acceptance and assimilation of e-learning systems in developing countries in general.

1.1. Related work

Mirza and Al-Abdulkareem [30] reviewed the current situation of e-learning in the Middle East (ME). They presented drivers and barriers to e-learning, the different types of e-learning initiatives, steps being taken toward overcoming the challenges, and a possible future of e-learning through a case study of ongoing developments of e-learning in Saudi Arabia. Educational organizations in the ME are varying in their engagement in e-learning as some are pioneering while the majority are progressing visa-vis those that are still laggards.

To provide more insight into how to promote e-learning acceptance among students in Saudi Arabia, Al-Harbi [7] investigated the factors that influence e-learning by analyzing the perceptions and attitudes of Saudi university students using a survey conducted to investigate the acceptance of e-learning as perceived by students. Al-Harbi used a combined factor model of the original TAM and the Theory of Planned Behavior (TPB) [3] to explain significant perceptional and attitudinal factors related to the acceptance of e-learning. The findings demonstrated that attitudes toward e-learning, subjective norms, perceived behavioral control as well as e-learning system attributes were critical determinants of students' behavioral intention to use e-learning.

Advanced technologies facilitating a new environment of higher education e-learning have been investigated in Saudi Arabia such as the adoption of smart phones and tablets which is known as mobile learning or m-learning [13,32,37]. These studies report prevailing of these technologies to some extent indicating that the acceptance and adoption level of m-learning is on rise as the majority of students express positive attitudes toward m-learning due to the flexibility of learning methods and timings, and improved communication among learners. However, Chanchary and Islam [13] pointed out that there are many more challenges still to overcome like giving proper training to students (a type of intervention as per TAM3) so they can have a sense of security in the new environment in an attempt to take full advantage of e-learning.

Jordan is a good example of developing countries in the ME, exemplifying an IT hub for the region, first introduced e-learning in the Arab Open University in 2002 [1]. Abbad et al. [1] and Al-Adwan et al. [4] explored students' acceptance of e-learning in Jordanian universities using the original TAM. Their findings, respectively, indicated that students' beliefs about usefulness and ease of use partially mediate the relationships between external factors (subjective norms, internet experience, system characteristics, self-efficacy, and technical support) and intention to use and actual use of e-learning systems; and that intention to use e-learning systems is only predicted by perceived usefulness as students' attitude did not significantly affect intention to use e-learning, while perceived ease of use was found to significantly predict both usefulness and attitude toward e-learning.

Lately, Singh and Hardaker [38] conducted a broad search of the literature (for more than 300 articles) regarding barriers and enablers to the adoption and diffusion of e-learning that were analyzed as three main categories: (1) macro-level studies investigating the higher education context of e-learning, (2) micro-level studies probing on individual and social factors, and (3) studies probing on management issues of the adoption and diffusion of technological innovations. Fortunately, our study seeks an empirical investigation of e-learning acceptance and assimilation using the Technology Acceptance Model (TAM3) as a framework covering the second and third categories suggested by Singh and Hardaker beforehand.

1.2. Theories of technology acceptance – Technology Acceptance Model 3

The original TAM [19,20] proposed that two belief constructs, perceived usefulness (PU) and perceived ease of use (PEOU), are primary determinants of an individual's behavioral intention (BI) to use an IT. BI was theorized as the primary predictor of actual usage behavior. There were successive developments of TAM: TAM2, UTAUT, and finally TAM3. Fortunately, the original TAM, TAM2 and UTAUT were tested in the Arabian context and showed to hold very well [5,9,6], respectively).

In this study, following Baker et al. [9], TAM3 is tested in the context of Saudi Arabia, a technologically-developing Arab nation. Since the Technology Acceptance Model is built on the foundation of an individual's beliefs, it is rational to expect that the application of any given Technology Acceptance Model in the two different cultural contexts could produce different results [9]. It is hoped that the findings of this study shall help to improve our understanding about the antecedents of e-learning technology acceptance and assimilation in Saudi Arabia, thereby providing us an opportunity to refine the model to suit this country's unique cultural context and offering a path to investigate technology adoption characteristics in other developing countries [5,9]. This paper was part of a scientific project which evolved over more than 3 years since 2010. The agenda for this project was summarized and published in the second international conference of e-learning and distance education by the ministry of higher education in Saudi Arabia [22].

1.3. Technology Acceptance Model 3 – TAM3

The most recent and comprehensive developments of TAM are manifested in TAM3. Venkatesh and Bala [44] synthesized prior research on TAM and developed a theoretical framework that represents the cumulative body of knowledge from TAM research that accumulated over the years, that results in four different types of determinants of PU and PEOU – *individual differences, system characteristics, social influence, and facilitating conditions*. According to Venkatesh and Bala [44], "individual difference variables include personality and/or demographics (e.g., traits or states of individuals, gender, and age) that can influence individuals' perceptions of PU and PEOU", while, "system characteristics are those salient features of a system that can help individuals develop favorable (or unfavorable) perceptions regarding the usefulness or ease of use of a system", whereas, "social influence captures various social processes and mechanisms that guide individuals to formulate perceptions of various aspects of an IT", finally, "facilitating conditions represent organizational support that facilitates the use of an IT" (p. 276). In summary, Venkatesh and Bala [44] combined TAM2 [42] and the model of the determinants of PEOU [41], and developed an integrated model of technology acceptance which they called: TAM3. TAM3 presents a comprehensive nomological network of the determinants of individuals' IT adoption and use, as shown in Fig. 1.

In the context of IT adoption and use, social influence processes (i.e., compliance, identification, and internalization) represent how important referents believe about the instrumental benefits of using a system [42]. Prior individual information and perceptions – about how easy a system is to use from important referents – are unlikely to be stable as individuals need to form these stable perceptions based on their own general computer beliefs and hands-on experience with the system [21]. In TAM3, three constructs – subjective norms (SN), image (IMG), and

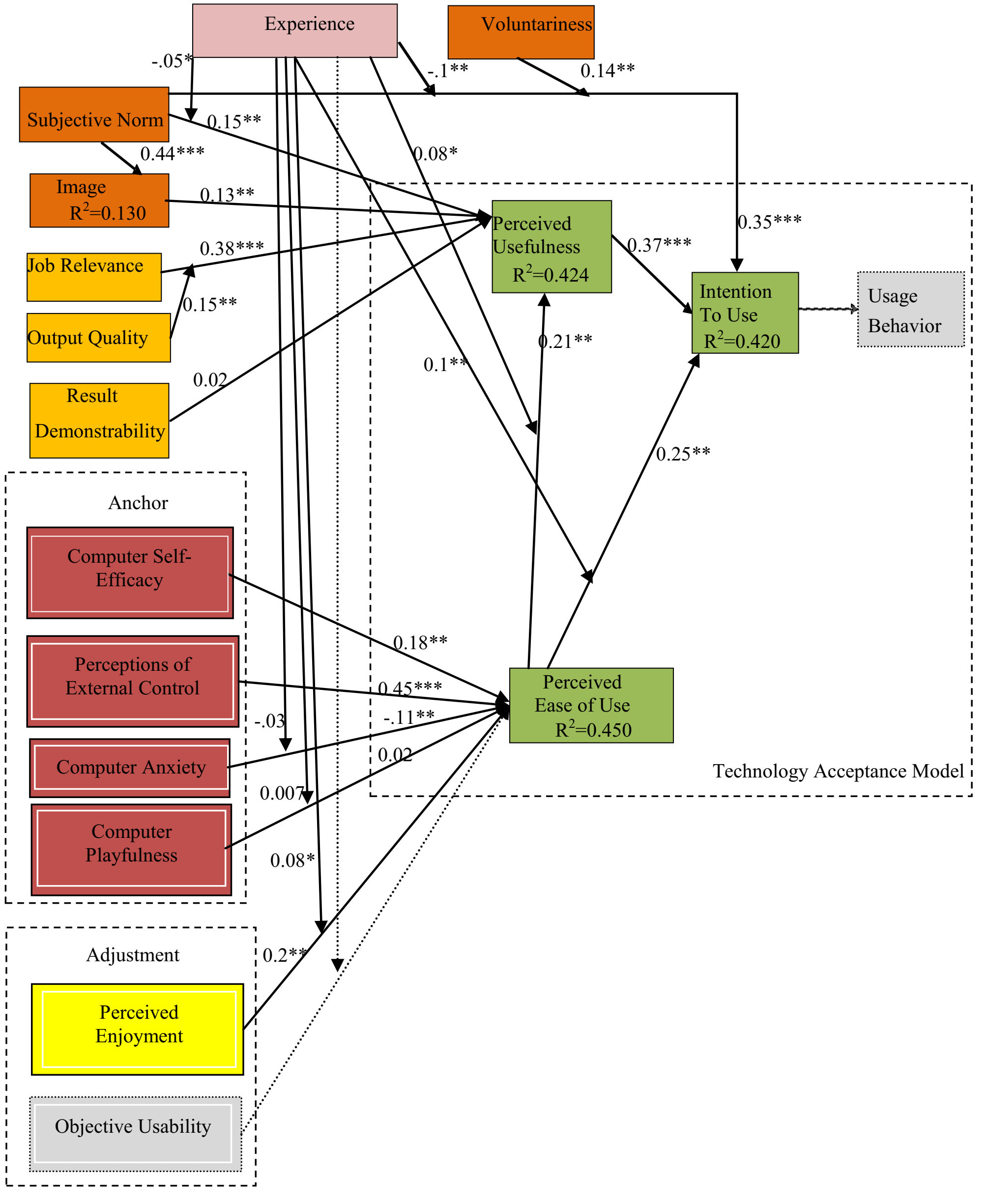

Figure 1 Research model – A modified Technology Acceptance Model 3 (TAM3)[a] – and structural model. [a]Dotted variables (Usage behavior and objective usability) are omitted. *Note:* All β for path coefficients are significant at $p < 0.05$ or better except coefficients of $\beta < \pm 0.04$.

voluntariness (VOL) – capture the social influence processes on perceived usefulness [44].

However, according to Venkatesh and Bala [44], the influence of cognitive instrumental processes on perceived usefulness is captured by four constructs:

job relevance, output quality, result demonstrability, and perceived ease of use. "The core theoretical argument underlying the role of cognitive instrumental processes is that individuals form perceived usefulness judgment in part by cognitively comparing what a system is capable of doing with what they need to get done in their job" [42, p. 190]. TAM3 theorizes that job relevance and result demonstrability directly affect perceived usefulness while output quality operates as a moderator of the relationship of job relevance with perceived usefulness. Table 1 presents the constructs definitions of social influence processes followed by the cognitive instrumental processes.

Four anchors were suggested by TAM3: "*computer self-efficacy, computer anxiety, computer playfulness,* and *perceptions of external control* (or *facilitating conditions*). The first three of these anchors represent individual differences (are) general beliefs associated with computers and computer use. Computer self-efficacy refers to individuals' *control* beliefs regarding his or her personal ability to use a system. Perceptions of external control are related to individuals' *control* beliefs regarding the availability of organizational resources and support structure to facilitate the use of a system. Computer playfulness represents the *intrinsic motivation* associated with using any new system" [44, p. 278]. Notably, Venkatesh and Bala [44] also suggested that "while anchors drive initial judgments of perceived ease of use, individuals will adjust these judgments after they gain direct hands-on experience with the new system" (p. 278).

Perceived enjoyment and objective usability were – two system characteristic-related adjustments – suggested by Venkatesh and Bala [44] to be included in TAM3 as determinants of perceived ease of use with enduring effects even after individuals gain experience with the new system. Following Venkatesh [41], Venkatesh and Bala [44] theorized that, in TAM3, the role of two anchors – computer self-efficacy and perceptions of external control – will continue to be

Table 1 Determinants of perceived usefulness [44, p. 277].

Determinants	Definitions
Perceived ease of use (PEOU)	The degree to which a person believes that using an IT will be free of effort [20]
Subjective norm (SN)	The degree to which an individual perceives that most people who are important to him think he should or should not use the system [23,42]
Image (IMG)	The degree to which an individual perceives that use of an innovation will enhance his or her status in his or her social system [31]
Job relevance (REL)	The degree to which an individual believes that the target system is applicable to his or her job [42]
Output quality (OQ)	The degree to which an individual believes that the system performs his or her job tasks well [42]
Result demonstrability (RES)	The degree to which an individual believes that the results of using a system are tangible, observable, and communicable [31]

strong despite user's gaining more experience with the system, in contrary, with the effects of the other two anchors – *computer playfulness and computer anxiety* – which were theorized to diminish over time. Moreover, TAM3 theorized that with more hands-on experience with the system, the effects of adjustments – *perceived enjoyment and objective usability* – on perceived ease of use were escalating. The constructs definitions of anchors and adjustments are shown in Table 2.

TAM received special attention from prominent scholars in the IS field. The Journal of the Association for Information Systems (JAIS) devoted a special critical issue (volume 8, issue 4, April 2007) about TAM "Quo Vadis TAM – Issues and Reflections on Technology Acceptance Model" [26]. The scholars' reviews varied dramatically from "TAM is a blessing and indisputable" on one end to "TAM is a curse" on the other end. TAM3 was first developed and published in May 2008 which resolved a number of shortcomings with the TAM model. Viswanath Venkatesh, Fred Davis (as the innovator of TAM), and Mike Morris commentary on the JAIS special issue was "We conclude that there has been excellent progress in technology adoption research. However, as a next step, we call for research focused on interventions, contingencies, and alternative theoretical perspectives (to the largely social psychology-based technology adoption research" [43, p. 267]. Hence, TAM3 came as a response to the JAIS special issue to focus on interventions, and therefore, we believe that TAM3 is a sound theoretical framework to investigate the factors affecting individual acceptance and assimilation of e-learning in various settings which is much more developed than previous editions of TAM. Several previous studies (e.g., [4,7,1,36] used old versions of TAM as a framework to study e-learning from different perspectives. Moreover, this study – to the best of our knowledge – is the first one to use the latest version of TAM (i.e., TAM3) as a framework to study e-learning.

Table 2 Determinants of perceived ease of use [44, p. 279].

Determinants	Definitions
Computer self-efficacy (CSE)	The degree to which an individual believes that he or she has the ability to perform a specific task/job using the computer [17,18]
Perception of external control (PEC)	The degree to which an individual believes that organizational and technical resources exist to support the use of the system [45]
Computer anxiety (CANX)	The degree of "an individual's apprehension, or even fear, when she/he is faced with the possibility of using computers" [41, p. 349]
Computer playfulness (CPLY)	"...the degree of cognitive spontaneity in microcomputer interactions" [47, p. 204]
Perceived enjoyment (ENJ)	The extent to which "the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use" [41, p. 351]
Objective usability (OU)	A "comparison of systems based on the actual level (rather than perceptions) of effort required to completing specific tasks" [41, pp. 350–351]

2. Research model and hypotheses

TAM3 is the most recent reformulation of TAM as reflected in the seminal work published by Venkatesh and Bala [44]. The nomological network of TAM3 as per Fig. 1 reveals that both social influence processes (subjective norm (SN), voluntariness (VOL) and image (IMG)) and cognitive instrumental processes (job relevance (REL), output quality (OQ), result demonstrability (RES), and perceived ease of use (PEOU)), establish the determinants of perceived usefulness (PU). The anchors (computer self-efficacy (CSE), perceptions of external control (PEC), computer anxiety (CANX), and computer playfulness (CPLY)), and the adjustments (perceived enjoyment (ENJ) and objective usability (OU)) establish the determinants of perceived ease of use (PEOU). PU, PEOU, and subjective norm (SN) determine behavioral intentions (BI) to use an IT. Ultimately, BI determines IT usage behavior. Venkatesh and Bala [44] reported that TAM3 accounted for 52–67% of the variance in usefulness perceptions, 43–52% of the variance in ease of use perceptions and 40–53% of the variance in usage intentions.

However, this study research model differs from TAM3 in three basic aspects. Firstly, in this study, our survey data on the model constructs were collected at a single point in time, as opposed to a longitudinal methodology (i.e., collecting several measurements over time). Our focus is on how well the social influence processes, the cognitive instrumental processes, the anchors and the adjustments predict e-learning technology acceptance, in particular the implicit cultural effects on these processes and factors which affect technology acceptance and assimilation. Secondly, the usage construct of TAM3 model was excluded, because we intend to collect cross-sectional data at a single time point, instead of longitudinally, the choice to measure technology acceptance with intention is appropriate, since measuring usage would require assessments of people's beliefs and attitudes in a preceding period. Thus, the use of intention is appropriate for our study and allows us to measure acceptance and beliefs contemporaneously [2].

Objective Usability (OU) used to be operationalized consistent with the keystroke model from human–computer interaction (HCI) research and prior user acceptance research [41]. The suggested guideline for operationalizing this construct is to compute a novice-to-expert ratio of effort. Specifically, the time taken by an expert to perform a set of tasks using the system in an error-free situation is compared with the time taken by a novice (subject) [41]. Accordingly, a set of e-learning tasks should be assigned and completed by the respondents (students). The time taken by each individual student to complete the tasks should be recorded by the Learning Management System (LMS), which will be compared later to the time taken by an expert to arrive at a ratio that would serve as the measure of OU for the particular subject (student). The higher the OU estimate (student-to-expert ratio), the harder the system is to use from an objective standpoint [41]. Unfortunately, the LMS technology used in our university (Blackboard) does not support the keystroke model to measure OU. Therefore, this construct was dropped from the research model which reflects the third difference of this study from TAM3.

In view of that, the current research main hypotheses are as follows:

H_1: The original TAM will hold well in the Saudi Arabian environment.
H_2: The extended TAM (TAM3) will hold well but differently from Western cultures (i.e., the culture where TAM3 originated).
H_3(a): The social influence process variable (SN) will significantly influence behavioral intention (BI) to use the e-learning system,
H_3(b): The social influence process variables (SN and IMG) will significantly influence perceived usefulness (PU) of the e-learning system,
H_3(c): The social influence process variable (IMG) will mediate the influence of subjective norm (SN) on perceived usefulness (PU) of the e-learning system,
H_3(d): The social influence process variable (VOL) will significantly moderate the influence of SN on behavioral intention (BI) to use the e-learning system,
H_4(a): The cognitive instrumental process variables (REL, RES, and PEOU) will significantly influence perceived usefulness (PU) of e-learning system,
H_4(b): The cognitive instrumental process variable (OQ) will significantly moderate the influence of JREL on perceived usefulness (PU) of the e-learning system,
H_5: The four anchor variables (CSE, PEC, CANX, and CPLY) will significantly influence perceived ease of use (PEOU) of the e-learning system,
H_6: The adjustment variable (ENJ) will significantly influence perceived ease of use (PEOU) of the e-learning system,
H_7: Experience (EXP) as a moderator in TAM3 will significantly moderate the seven intended paths as shown in Fig. 1.

3. Research methodology

3.1. Sampling procedure

A "convenience sample" amalgamated with "quota sample" was thought to be the most appropriate sampling procedure for this study. Convenience sampling was deemed appropriate by the virtue of the researcher's accessibility to the respondents while quota sampling was considered appropriate in terms of achieving relative proportions of respondents in different categories such as gender, course major, and study level [12]. Six sites, (three male colleges: Science, Business, and Engineering, and three female colleges: Science, Arts and Literature, and Girls' Study Center), as subsidiaries of a large Saudi Arabian university in the southern region, were chosen according to this sampling procedure for data collection. These sites were mature in e-learning experience and provided with high speed internet connectivity. To achieve this goal, the data collection method thought to be most appropriate was a survey questionnaire. Newsted et al. [33] argue that surveys are among the more popular methods used by the information systems (IS) research community.

3.2. Structural Equation Modeling approach

Structural Equation Modeling (SEM) techniques are a second-generation multivariate technique [24] that has been widely used for instrument validation and model testing in research in the field of marketing and organizational behavior. The SEM technique has also been introduced to MIS and started gaining popularity among researchers in the field who have adopted this approach in several studies recently reported in the literature. Conceptually and practically, SEM is similar to using Multiple Regression Analysis (MRA). However, causal models developed following the SEM approach are superior to MRA in many ways. As this study seeks a causative explanation of the decision behavior of individuals toward the acceptance and assimilation of e-learning, SEM came in front of other potential approaches to achieve this purpose. Chau et al. [14] reported that Bagozzi [8] enumerated the advantages that causal models developed using the SEM approach possesses, such as: "(1) they make the assumptions, constructs, and hypothesized relationships in a researcher's theory explicit; (2) they add a degree of precision to a researcher's theory, since they require clear definitions of constructs, operationalizations, and the functional relationships between constructs; (3) they permit a more complete representation of complex theories; and (4) they provide a formal framework for constructing and testing both theories and measures" [14, p. 314].

The most widely used statistical software packages that adopt the SEM approach include LISREL and PLS. Although they are both SEM based, they are quite different in their estimation approaches and objectives. The primary measures used in LISREL are overall goodness-of-fit measures that assess how well the hypothesized model fits the observed data. Hence, the analysis is "theory-oriented, and emphasizes the transition from exploratory to confirmatory analysis" [29, p. 270]. PLS-based structural equation modeling (PLS-SEM) is based on least squares estimation with the primary objective being to maximize the explanation of variance in the dependent constructs of a structural equation model. PLS is essentially targeted for causal-predictive analysis as PLS is more appropriate to analyze highly complex causal models with low theoretical substantiation for the purpose to maximize the determinants' predictive power toward the dependent construct.

In summary, the researcher decided to use PLS-SEM to analyze this study data for several reasons:

1) PLS-SEM is, as the name implies, a more "regression-based" approach that minimizes the residual variances of the endogenous constructs [25].

2) Indeed, TAM3 is relatively a new theoretical model developed by Venkatesh and Bala [44] that presently undergoes empirical test in the Arabian culture. Because of its prediction orientation, PLS-SEM is, thus, the preferred method when the research objective is theory development and prediction [25].
3) PLS-SEM can be a powerful method of analysis because of the minimal demands on measurement scales, sample size, and residual distributions [15]. In fact, our study sample size is comparatively small with skewed variables indicating that it is not normally distributed.
4) Hair et al. [25] conclude that PLS-SEM path modeling, if appropriately applied, is indeed a "silver bullet" for estimating causal models in many theoretical models and empirical data situations.

3.3. Research instruments

All the survey items used to operationalize the constructs investigated in our research model were adapted for this study from Venkatesh and Bala [44]. However, these scales were originally developed and tested in the English language, and therefore developed in a different environment and culture. To adapt them for the current research in Arabic, the Brislin [11] back translation method was used. The items were translated back and forth between English and Arabic by two teams of bilingual professors. The process was repeated until both versions converged. The Arabic version instruments that emerged were subject to two Arabic judges to make sure that the instruments are suitable for application for the present research project.

4. Data analysis

4.1. Sample analysis

Six hundred copies of a five page questionnaire were distributed among the targeted six colleges. The returned and usable responses were 286, thus achieving a response rate of 47.67%. Table 3 shows the sample distribution by gender and study major.

5. Results

Following Baker et al. [9], the research model shown in Fig. 1 was analyzed using SmartPLS 2.0, a Partial Least Squares (PLS) structural equation modeling (SEM) software tool Ringle et al. [35]. One of the essential features of SmartPLS is the simultaneous assessment of the psychometric properties of the *measurement model* (i.e., the reliability and validity of the scales used to measure the model variables), as well as the estimation of the parameters of the *structural model* (i.e., the strength

Table 3 Respondents distribution by gender and study major.

Category					Total
Gender	Male(164) 57.34%	Female(122) 42.66%			(286) 100%
Study major	Business (125) 43.71%	Engineering (82) 28.67%	Sciences (48) 16.78%	Arts & Literature (31) 10.84%	(286) 100%

of the path relationships among the model variables). The subsequent paragraphs present the analysis results of the psychometric properties of the measurement model and the estimation of the parameters of the structural model.

5.1. The measurement model

The measurement model testing results revealed a strong evidence of the robustness of the constructs' measures denoted by their internal consistency reliabilities as manifested by their composite reliabilities presented in Table 4. The range of the composite reliabilities of the measures was 0.70–0.91. Almost all of these reliability indices properly exceed the threshold of 0.70 recommended by Nunnally [34]. Additionally, the average variance extracted (AVE) for each measure far exceeds the lower bound threshold value of 0.50 recommended by Fornell and Larcker [24], as the AVEs for the measurement constructs ranged from 0.763 to 0.919.

Smart PLS generates the convergent validity tests of the scales by extracting the factor loadings and cross loadings of all items (indicators) to their own respective constructs. Table 5 presents these results indicating that all items (after dropping two items: CSE1 and ENJ3): (1) loaded on their own particular constructs from a lower bound of 0.700 to an upper bound of 0.909 (the bolded factor loadings), and

Table 4 Assessment of the measurement model.

Variable constructs	# of items	Mean	Variance	Std. deviation	Average variance explained (AVE)	Discriminant validity	Composite reliability (internal consistency reliability)
Behavioral intention	3	13.39	20.23	4.50	0.861	0.93	0.80
Computer anxiety	3	9.67	31.90	5.65	0.851	0.92	0.91
Job relevance	3	10.53	20.56	4.53	0.919	0.96	0.90
Computer playfulness	3	13.35	23.83	4.88	0.879	0.94	0.83
Computer self-efficacy	3	17.54	46.11	6.79	0.815	0.89	0.71
Enjoyment	2	8.33	10.54	3.25	0.882	0.93	0.85
Ease of use	3	17.72	27.99	5.29	0.827	0.91	0.75
Image	3	11.05	24.37	4.94	0.884	0.94	0.85
Perception of external control	3	9.81	9.08	3.01	0.763	0.87	0.70
Result demonstrability	3	13.26	17.09	4.13	0.845	0.92	0.76
Subjective norm	4	7.76	13.03	3.61	0.818	0.90	0.86
Usefulness	4	17.17	35.40	5.95	0.904	0.95	0.90

Table 5 Factor loadings (bolded) and cross loadings.

	Beh. int.	Comp. anx.	Job. relv.	Comp. ply.	Comp. self. eff.	Enjoyment	Ease of use	Image	Per. ext. ctrl.	Result demo.	Subj. norm	Usefulness
BI1	**0.822**	−0.191	0.448	0.373	0.142	0.366	0.398	0.294	0.391	0.360	0.431	0.421
BI2	**0.766**	−0.204	0.399	0.332	0.292	0.386	0.391	0.215	0.228	0.341	0.344	0.305
BI3	**0.873**	−0.211	0.515	0.376	0.187	0.474	0.413	0.242	0.366	0.388	0.451	0.516
CANX1	−0.242	**0.802**	−0.253	−0.283	−0.207	−0.196	−0.333	0.029	−0.260	−0.188	−0.159	−0.150
CANX2	−0.117	**0.745**	−0.204	−0.262	−0.081	−0.189	−0.126	0.135	−0.174	−0.237	0.047	−0.057
CANX3	−0.193	**0.766**	−0.219	−0.233	−0.110	−0.208	−0.139	0.138	−0.152	−0.276	0.017	−0.091
CANX4	−0.133	**0.753**	−0.203	−0.280	−0.056	−0.208	−0.145	0.180	−0.212	−0.254	0.042	−0.105
REL1	0.502	−0.311	**0.864**	0.469	0.250	0.508	0.509	0.274	0.453	0.383	0.410	0.501
REL2	0.447	−0.251	**0.909**	0.408	0.202	0.487	0.445	0.289	0.396	0.368	0.345	0.546
REL3	0.538	−0.226	**0.894**	0.451	0.220	0.464	0.463	0.354	0.398	0.372	0.386	0.533
CPLY1	0.351	−0.323	0.361	**0.767**	0.317	0.320	0.250	0.118	0.289	0.239	0.204	0.263
CPLY2	0.373	−0.257	0.427	**0.886**	0.260	0.433	0.373	0.178	0.400	0.223	0.213	0.399
CPLY3	0.388	−0.313	0.460	**0.866**	0.248	0.462	0.325	0.167	0.337	0.261	0.206	0.392
CSE2	0.187	−0.123	0.167	0.273	**0.700**	0.121	0.255	−0.018	0.173	0.207	0.124	0.142
CSE3	0.189	−0.180	0.128	0.209	**0.701**	0.112	0.204	0.119	0.168	0.128	0.014	0.138
CSE4	0.199	−0.143	0.210	0.257	**0.729**	0.193	0.269	0.110	0.232	0.154	0.083	0.228
ENJ1	0.487	−0.317	0.507	0.445	0.176	**0.906**	0.437	0.200	0.399	0.265	0.290	0.595
ENJ2	0.427	−0.192	0.479	0.428	0.158	**0.876**	0.348	0.286	0.331	0.243	0.312	0.530
PEOU1	0.397	−0.187	0.431	0.324	0.338	0.362	**0.787**	0.173	0.445	0.300	0.235	0.485
PEOU3	0.336	−0.270	0.394	0.291	0.235	0.335	**0.807**	0.045	0.491	0.297	0.230	0.298
PEOU4	0.406	−0.231	0.419	0.282	0.236	0.312	**0.758**	0.169	0.491	0.328	0.322	0.321
IMG1	0.223	0.140	0.233	0.120	0.073	0.233	0.140	**0.858**	0.179	0.078	0.320	0.267
IMG2	0.268	0.124	0.249	0.167	0.066	0.230	0.130	**0.867**	0.152	0.062	0.296	0.256
IMG3	0.281	0.058	0.381	0.185	0.094	0.271	0.156	**0.817**	0.158	0.081	0.299	0.343
PEC1	0.217	−0.225	0.309	0.295	0.250	0.237	0.525	0.109	**0.811**	0.296	0.276	0.267
PEC2	0.305	−0.162	0.401	0.318	0.084	0.307	0.382	0.156	**0.732**	0.360	0.344	0.437
PEC3	0.393	−0.210	0.318	0.286	0.221	0.327	0.382	0.167	**0.706**	0.116	0.169	0.377
RES1	0.327	−0.241	0.276	0.210	0.143	0.221	0.296	0.048	0.309	**0.792**	0.305	0.227
RES2	0.307	−0.203	0.319	0.230	0.210	0.263	0.294	0.062	0.283	**0.826**	0.238	0.245
RES3	0.414	−0.252	0.404	0.240	0.169	0.206	0.352	0.096	0.277	**0.793**	0.383	0.279
SN2	0.430	0.027	0.291	0.198	0.058	0.339	0.262	0.297	0.254	0.268	**0.740**	0.303
SN3	0.306	−0.151	0.346	0.155	0.131	0.211	0.221	0.195	0.243	0.367	**0.743**	0.336
SN4	0.402	−0.222	0.345	0.219	0.086	0.249	0.311	0.186	0.355	0.362	**0.745**	0.334
PU1	0.399	−0.053	0.475	0.331	0.168	0.478	0.347	0.319	0.358	0.282	0.378	**0.838**
PU2	0.386	−0.126	0.456	0.322	0.149	0.506	0.401	0.243	0.427	0.279	0.362	**0.867**
PU3	0.413	−0.091	0.489	0.345	0.244	0.487	0.376	0.286	0.428	0.229	0.291	**0.863**
PU4	0.504	−0.197	0.551	0.412	0.221	0.519	0.457	0.298	0.397	0.261	0.333	**0.783**

(2) loaded more highly on their own particular construct than on any other construct (the non-bolded factor loadings). According to Yoo and Alavi [40], a common rule of thumb to indicate convergent validity is that all items should load greater than 0.7 on their own construct, and should load more highly on their own respective construct than on the other constructs. Moreover, our measurement analysis shows that each item's factor loading on its respective construct was highly significant ($p < 0.001$). Table 4 presents the loadings confirming the convergent validity of the measures for the research model latent constructs.

5.2. The structural model

The results of the structural model are presented in Fig. 1. The direct influence of each exogenous construct on the endogenous construct is indicated by the beta value of the path coefficient presented numerically on the solid arrow leading from the exogenous construct to the endogenous construct with asterisk(s) of the significance level. Those insignificant relationships are presented in dotted arrows. The following is a summary of the significant connections between the factors of our study. The current research findings confirm that BI (as the primary dependent factor) is predicted by three factors: PU, PEOU and SN whereas PEOU is significantly moderated by experience while SN is significantly moderated by both experience and voluntariness. PU is predicted by PEOU, SN, Image, and job relevance whereas PEOU and SN are significantly moderated by experience while job relevance is significantly moderated by output quality. Finally, PEOU is predicted by computer self-efficacy, perceptions of external control, computer anxiety, and perceived enjoyment with the latter significantly moderated by experience. Details are found in the discussion and implications section. Fig. 1 also presents the variance explained (R^2) in each of the four endogenous constructs by their predictors.

6. Discussion and implications

In interpreting the results presented in Fig. 1, this study draws on the guidelines provided by Chin et al. [15]. The results of the direct and moderator effects and post-implementation interventions are discussed subsequently.

6.1. Direct effects

All of the direct relationships between the core constructs of the original TAM exhibited strong positive effects. More specifically, *perceived ease of use* (PEOU) attained a strong positive direct influence on PU (beta = 0.206, $p < 0.001$). In addition, PEOU simultaneously showed a strong direct effect on *behavioral intention* (BI) (beta = 0.252, $p < 0.001$). PU achieved a strong positive direct influence on BI (beta = 0.374, $p < 0.001$). These results strongly indicate that the original TAM holds very well in the Arabian culture. Hence, $\mathbf{H_1}$ is supported.

Additionally, our finding related to the PU strong impact on BI supports similar findings by Al-Adwan et al. [4].

All social influence process variables and all cognitive instrumental process variables (except result demonstrability) exhibited significant relationships as determinants of perceived usefulness. Also, all anchor variables (except CPLY) and computer enjoyment as the single adjustment variable exhibited significant relationships as determinants of perceived ease of use. Besides that, experience exhibited five out of seven significant moderating relationships specified in TAM3. Furthermore, by comparing the variance explained (R^2) in this study vs. TAM3: BI (0.420/0.400), PU (0.424/0.520), and PEOU (0.450/0.440), respectively, one can conclude that they are similar with regard to BI and PEOU but different in PU. As a result, TAM3 holds well in the Arabian context but somehow differently from Western cultures (i.e., the culture where TAM3 originated).

The main dependent variable in this study is behavioral intentions (BI) of students to accept and use an e-learning system which solely predict and determine actual system usage and, consequently, the success of new ITs, as per TAM3. However, rather than PU which exhibits the strongest influence on BI in Western culture, this study reports that subjective norm (SN) exhibits the strongest influence on BI (beta = 0.349, $p < 0.001$ compared to the insignificant SN → BI relationship in (TAM3: Venkatesh and Bala [44]). Indeed our finding confirms a pronounced effect of SN on BI in Saudi Arabia, a finding which is not usually observed in Western contexts. This adds further evidence and supports the important role of SN reported by Al-Harbi [7]. Therefore, $\mathbf{H_2}$ is supported.

Social influence captures various social processes and mechanisms that guide individuals to formulate perceptions of various aspects of an IT. Social influence processes (SN, IMG, VOL) proved to significantly affect perceived usefulness both direct (SN → PU = 0.349, $p < 0.001$ and IMG → PU = 0.133, $p < 0.001$) and moderating relationships (by EXP and VOL) besides SN to significantly affect BI both direct (SN → BI = 0.349, $p < 0.001$) and moderating relationships (by EXP and VOL) to be explained below. Additionally, SN → IMG relationship is significant (SN → IMG = 0.435, $p < 0.001$). Therefore, $\mathbf{H_3}$**(a)**, $\mathbf{H_3}$**(b)**, $\mathbf{H_3}$**(c)** are fully supported.

TAM2 postulates that three social influence mechanisms – compliance, identification, and internalization – will play a role in understanding the social influence processes [42]. These three mechanisms can be briefly interpreted in the context of IT adoption and use such that: *compliance*: represents a situation in which an individual adopts and uses an IT in order to attain certain rewards or avoids punishment; whereas *identification* refers to an individual's belief that adopting and using an IT will elevate his or her social status within a referent group because important referents believe s/he should do so; however, *internalization* is defined as the incorporation of a referent's belief into one's own belief structure. This would ensure the adherence to the compliance and identification of the social influence mechanisms. However, the internalization mechanism will be manifested as a result of continuous adherence of individuals to the compliance and identification mechanisms as it is expected that with time the incorporation of important referent's belief into one's own belief structure will take place.

We believe that underpinning the notion of IT acceptance and assimilation onto these three social influence mechanisms in the bounds of Saudi Arabia's cultural context with the pervasiveness of the Saudi hierarchical conforming society in the workplace [10] would open a new outlook in this issue. Accordingly, we contend that Saudi individuals would show a high regard for authority and would conform to the expectations of those elites/managers who occupy senior roles in the organizational hierarchy while embracing IT take-up tendency, would lead to IT acceptance and assimilation. This perspective is "especially true in light of the heavy promotion of technology adoption through governmental policy and where there are typically more rigid cultural and organizational structures of authority between managers and subordinates" [9, p. 49].

In TAM3, four constructs – job relevance, output quality, result demonstrability, and perceived ease of use – capture the influence of cognitive instrumental processes on perceived usefulness. This study proved that two cognitive instrumental processes (REL and PEOU) significantly affect perceived usefulness as per TAM3 (REL → PU = 0.380, $p < 0.001$; PEOU → PU = 0.206, $p < 0.001$) while OQ significantly moderate REL → PU relationship (explained below). Result demonstrability (RES) was the only exception, as RES did not significantly affect PU which might indicate that participants do not believe that the results of using the LMS are tangible, observable, and communicable [31]. Hence, $\mathbf{H_4(a)}$ is partially supported.

The anchors suggested by TAM3 are *computer self-efficacy, computer anxiety, perceptions of external control* (or *facilitating conditions),* and *computer playfulness*. The first three of these anchors proved to significantly affect PEOU in this study (CSE → PEOU = 0.176, $p < 0.001$; CANX → PEOU = –0.105, $p < 0.05$; PEC → PEOU = 0.454, $p < 0.001$). However, computer playfulness did not significantly affect PEOU indicating the absence of *intrinsic motivation* associated with using the LMS. Perceptions of external control exhibited the strongest effect among anchors indicating how individuals' *control* beliefs regarding the availability of organizational resources and support structure facilitate the use of the system. This finding supports the important role of perceptions of external control reported by Al-Harbi [7]. Hence, $\mathbf{H_5}$ is partially supported.

As indicated earlier, only one system characteristic-related to adjustments – that is, *perceived enjoyment* – was investigated in this study which proved to play a considerable role in determining perceived ease of use after individuals gain experience with the system. This study proved that enjoyment significantly affects PEOU (ENJ → PEOU = 0.201, $p < 0.001$). Therefore, $\mathbf{H_6}$ is supported.

6.2. Moderators effects

TAM3 posits that subjective norm (SN) has a positive significant effect on behavioral intention (BI) and to continue in voluntary usage contexts. Our findings indicate that SN has positive direct effect on BI and that voluntariness (VOL) positively moderates the effect of SN on BI (VOL × SN → BI = 0.14) indicating that the positive direct effect of SN on BI will not attenuate in voluntary usage contexts. The positive interaction of voluntariness on the effect of SN on BI could be interpreted such that, users in more voluntary usage contexts are inclined to be positively affected by significant others' opinions regarding their intention to use LMS. In this milieu, it is likely that the effect of subjective norm on intention to use LMS will not diminish with increasing voluntariness, as reported in Venkatesh and Davis [42]. Specifically, they found that SN influenced BI only in mandatory usage contexts, and that in voluntary usage contexts, SN had no direct effect on BI. We contend that the significant effect of SN on BI, in both mandatory and voluntary usage contexts, can be explained within Saudi Arabia's cultural context. In light of these Saudi cultural impacts, even if the context of usage was voluntary, SN would continue to be a significant predictor of BI. Indeed, our findings do confirm a pronounced effect of SN on BI in Saudi Arabia, a finding which is not usually observed in Western contexts. Hence, **H_3(d)** is supported.

Venkatesh and Davis [42] defined job relevance as the degree to which an individual believes that the target system is applicable to his or her job. This study reports on a strong positive direct effect of job relevance (REL) on perceived usefulness (PU) that will increase with higher output quality. OQ positively moderated the effect of REL on PU (OQ x REL → PU = 0.152). Job relevance and output quality will have a moderating effect on perceived usefulness such that the higher the output quality, the stronger the effect job relevance will have on perceived usefulness as reported in Venkatesh and Davis [42]. Thus, **H_4(b)** is supported.

The positive direct effect of subjective norm on both behavioral intention and perceived usefulness will attenuate with increased experience. EXP negatively moderated the effect of SN on BI (EXP × SN → BI = −0.10) and PU (EXP × SN → PU = -0.05). These relationships are supported. These negative coefficients could be interpreted to indicate that more experienced individuals are possessing stable perceptions about LMS usefulness besides their affirmed intention to use LMS regardless of referent opinion in this issue. In other words, more experienced users' tendencies are less likely to be affected by significant others' opinions regarding their perceptions of LMS usefulness and their intention to use LMS. In this context, contrary to the findings of [42], our findings indicate that it is likely that the effect of subjective norm on perceived LMS usefulness and on intention to use LMS will diminish as users gain more experience with the system. Hence, management should concentrate on users to acquire more experience with the system, instead of relying on referent opinions, to ensure higher levels of system acceptance and assimilation.

The positive direct effect of ease of use on both behavioral intention and perceived usefulness will *not* attenuate with increased experience. EXP positively moderated the effect of EOU on BI ($EXP \times PEOU \rightarrow BI = 0.101$) and PU ($EXP \times PEOU \rightarrow PU = 0.083$). These relationships are supported. We interpret these positive coefficients as an indication that more experienced individuals are still inclined to be affected by significant system ease of use regarding the perceived usefulness of, and intention to use, LMS. In this context, it is likely that the effect of ease of use on perceived usefulness and intention to use a system will *not* diminish with increased experience. In fact our findings confirm a pronounced effect of PEOU on both PU and BI in Saudi Arabia, which should not be overlooked during system design.

EXP did not significantly moderate the negative influence of computer anxiety (CANX) on PEOU ($EXP \times CANX \rightarrow PEOU = -0.035$). In this context, it is less likely that the effect of computer anxiety on system ease of use will diminish with increasing experience, as reported in Venkatesh and Davis [42]. This is a sign of the impediment effect of anxiety with LMS users which persists even with increasing experience. However, EXP did *positively* moderate the positive influence of enjoyment (ENJ) on PEOU ($EXP \times ENJ \rightarrow PEOU = 0.076$). Hence, it is likely that the effect of system enjoyment on ease of use will increase with increased experience, as reported in Venkatesh and Davis [42].

Computer playfulness (CPLY) is theorized to significantly affect perceived ease of use (PEOU) as per TAM3. However, our findings indicate that computer playfulness fails to impact LMS ease of use which indicates that participants couldnot achieve an acceptable level of intrinsic motivation while using the LMS in order to foster their perceptions regarding LMS ease of use. Thus, users feel that the system has no playfulness merit which otherwise would let users to perceive the system as easy to use rather than being awkward and complex. This situation did not change when the $CPLY \rightarrow PEOU$ relationship was moderated by experience ($EXP \times CPLY \rightarrow PEOU = 0.007$). The insignificant interaction of experience on the effect of CPLY on PEOU could be interpreted such that, gaining more experience has an unconstructive role with regard to how computer playfulness impetus LMS' ease of use. In other words, even experienced users still perceive LMS with no playfulness merit because they couldnot achieve an acceptable level of intrinsic motivation which in turn fails to influence their perceptions regarding LMS ease of use.

Venkatesh [41] posited that the effects of adjustments on perceived ease of use (PEOU) were stronger with more hands-on experience with the system. Our study confirmed that the positive effect of enjoyment (ENJ) on PEOU ($ENJ \rightarrow PEOU$) relationship was significant when moderated by EXP ($EXP \times ENJ \rightarrow PEOU = 0.076$, $p < 0.05$). Although this study lacks a longitudinal merit, our findings indicate that more experienced users will enjoy using the system which will enable them to perceive the system as more easy to use. In summation, experience (EXP) as a moderator variable was significantly moderating five paths of the seven relationships identified in TAM3 as shown in Fig. 1. Therefore, $\mathbf{H_7}$ is partially supported.

7. Interventions

It has been advised by academics and practitioners that managers need to develop and implement effective *interventions* in order to maximize end-users' IT adoption and use [28]. Therefore, identifying interventions that could influence adoption and use of new ITs can aid managerial decision making on successful IT implementation strategies [28]. TAM3 paved the way to comprehend the role of interventions in IT acceptance and assimilation contexts, based on delineating the predictors of PU and PEOU. In TAM3, Venkatesh and Bala [44] classified interventions into two categories: *pre-implementation* and *post-implementation* interventions motivated by the stage models of IT implementation and type of intervention (e.g., design characteristics, user participation, incentive alignment, training, organizational and peer support). TAM3 also contributes to management with respect to interventions by supporting managerial decision making with two complementing alternatives [44]: Firstly, managers are provided with a framework to decide what interventions to apply during pre- and post-implementation stages and for what types of systems. Secondly, managers can decide on resource allocation for each specific intervention anchored by the impact of such intervention on different determinants of IT acceptance and assimilation, and system type.

As noted earlier, this study has the shortcoming of lacking a longitudinal merit and thus cannot justify *pre-implementation* interventions from the field. However, participants clearly acknowledged that they strongly desire to be given the choice between LMS alternatives based on ample presentations and demonstrations in order to alleviate initial resistance and develop genuine perceptions of system features, capabilities, and relevance to enhance future system acceptance and assimilation.

7.1. Post-implementation interventions

Post-implementation interventions represent a set of organizational, managerial, and support activities that take place after the deployment of a system to enhance the level of system acceptance by users [44]. Post-implementation interventions can be vital so that users are able to go through the initial shock and react favorably to changes associated with the new system. The core theme of post-implementation interventions should be to make users feel that the new system is an opportunity to enhance their job performance, and give them the ability and necessary resources to use the new system smoothly [44]. TAM3 suggests a group of post-implementation interventions: training, organizational support, and peer support that will be particularly relevant to each of the determinants of PU and PEOU.

In the following, we reflect on the concept of post-implementation interventions to our study findings by giving an example of one determinant of perceived usefulness and one determinant of perceived ease of use which were not significant and apply the suitable intervention, as alleviation, to each case.

(a) Our study reports that result demonstrability as a predictor of perceived usefulness was not significant which might indicate that participants do not believe that the results of using LMS are tangible, observable, and communicable [31]. In order to alleviate this situation, TAM3 suggests a bunch of post-implementation interventions such as: training, organizational support, and peer support which will be particularly relevant in this situation.
(b) Our study reports that computer playfulness as a predictor of perceived ease of use was not significant which might indicate that participants could not achieve an acceptable level of intrinsic motivation while using the LMS so as to perceive LMS as easy to use. In order to soothe this situation, TAM3 suggests training as the sole post-implementation intervention which will be particularly relevant and adequate to let users feel spontaneous and playful while using the system.

8. Limitations

Our study has its own limitations. This study was set to utilize TAM3 to empirically investigate the acceptance and assimilation of e-learning in a developing country. However, our study is not an exact replication of the study conducted by Venkatesh and Bala [44] to develop TAM3. Our study applied cross-sectional design and used a sample from a single organization compared to the Venkatesh and Bala study which used a longitudinal design with a sample of subjects included from four different organizations. Venkatesh and Bala [44] used conventional regression analysis (MRA), as the statistical technique to analyze their data. In contrast, our study employed PLS-based structural equation modeling (PLS-SEM), a more powerful technique to conduct the data analysis. We hope this analytical technique is a credit providing additional support for the validity of the results of our model.

With this study only having tested a single LMS technology (Bb) in one developing country, the generalizability of our findings are quite limited as well. There is a need to conduct additional studies applying TAM3 to developing nations to gain further support for the findings of this study as discussed below in the future studies of e-learning acceptance.

8.1. Future studies of e-learning acceptance

Singh and Hardaker [38] suggest that future studies of e-learning acceptance should target both the micro-level reflecting on several aspects such as: individualist perspective considering the different backgrounds, experiences and motivations of individual academics; and the macro-level considering various organizational and environmental settings. This study supports this recommendation and suggests that future research needs to close the gap between these two approaches by developing a more integrated theoretical framework that provides a means to diminish the overshadow effects of organizational roles and organizational and environmental settings over the personal characteristics inspiring fruitful future research findings.

Additionally, future studies could be conducted to examine TAM3 using samples of students and instructors from different geo-locations and a wider range of e-learning systems. This could involve testing TAM3 by including the technology usage behavior construct omitted from our research model, which would increase the predictable levels of e-learning acceptance. Furthermore, the full TAM3 model could be tested in future studies by including the objective usability construct which needs special research design to enable the key stroke model which we referred to in the research method above.

9. Conclusions

Contemporary organizations spend vast amounts of resources in ITs which are becoming progressively complex, and implementation costs are tremendously escalating with time. Implementation failures of many of today's ITs cost millions of dollars to organizations. In addition, low acceptance and adoption manifested in high underutilization of ITs have been a major problem for organizations.

This study develops our understanding of the determinants of e-learning acceptance and assimilation in a developing country by testing a nomological network based on TAM3 using structural equation modeling. It also partially advocates the concept of interventions – as per TAM3 – that can favorably influence these determinants so that management can proactively decide on implementing the right interventions to minimize resistance to this relatively new IT, and maximize its effective utilization.

All hypotheses of direct effect relationships, as per TAM3 in Fig. 1, were supported except two relationships: computer playfulness (CPLY) → perceived ease of use (PEOU) and result demonstrability (RES) → perceived usefulness (PU). Seven out of nine hypotheses of moderating effects relationships, as per TAM3 in Fig. 1, were supported. We hope that this adds further confidence in our research design and we also hope that future studies can refer to these findings for comparison and discussions.

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