Are Computer Experience and Anxiety Irrelevant? Towards a Simple Model for Adoption of E-Learning Systems

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Aamer Hanif (✉)
Air University, Islamabad, Pakistan
ahanif@mail.au.edu.pk

Ahmed F. Siddiqi
University of Central Punjab, Lahore, Pakistan

Zunera Jalil
Air University, Islamabad, Pakistan

Abstract—Massive growth of technology-based e-learning systems is enabling student access to academic content from higher education institutions around the world. This study explores the antecedents of behavioral intention of students to use e-learning systems in university education to supplement classroom learning. A quantitative approach involving a structural equation model is adopted and research data collected from 358 undergraduate students is used for analysis. The study framework is based upon the technology acceptance model (TAM) and three external factors are proposed to influence the behavioral intention of students to use e-learning. Frequently used external factors in previous researches like computer experience and anxiety were not used and alternate factors were explored. Research results show that self-efficacy, enjoyment and results demonstrability have a significant positive influence on perceived usefulness and on perceived ease of use of the e-learning system. Based upon these factors, a simplified model of e-learning systems adoption is proposed. The study identifies these contributory factors from the viewpoint of a student by suggesting that these factors are significant for undergraduate students.

Keywords—Technology acceptance, e-learning systems, behavioral intention

1 Introduction

Innovations and advances in instructional technologies integrated with higher education programs make them effective to enhance student learning. There is a continuing research effort in application of mobile-based multimedia technologies to

higher education. Students have massive opportunities to learn the same material that could be acquired by attending a class physically. In Pakistan, innovative technologies are posing challenges in terms of their adoption specifically for educational purposes and are placing unique demands on students to use them effectively. In presence of e-learning technologies, student motivation was a significantly affecting student achievement, mature students had better performance in enrolled courses and the ability to use ICT and digital technologies had a positive influence on student achievement [1]. Past research shows that using technology in education for lecture preparation, delivery, collaborative teamwork and motivating students to use self-regulated strategies for learning have a significant impact on effectiveness of courses [2].

Handheld smart devices provide students to remain updated with course material and allow additional opportunities to explore resources for learning. Interaction among students by using these technologies enable real time discussions, chances to brainstorm and harmonize their thoughts, and motivate them to experience resources that provide an enriched learning experience [3][4]. Learning support systems like Blackboard and Google Classroom allow quick availability of instructional material, ways to undertake assessment and provide feedback to students [5]. Additionally, they support discussions, collaboration between students, access to course teachers and assistants making these an important component of technology enabled instruction delivery in higher education system [6][7]. Other advantages include quick access to course materials, forums providing interaction opportunities with course staff, information sharing and different ways of providing educational content thereby enabling students to learn in their own time as needed [8]. With new technological innovations coming, their application in higher education will always remain a relevant area for research since a study of their enabling external factors will always be of importance. The question of identification of factors that motivate students to accept and use new technologies for learning has been widely studied [9]. However, in recent studies, the key focus has been on factors that have been frequently studied in the past making them more important due to their frequent use in models of technology acceptance and adoption. Factors like computer anxiety and experience are frequently explored in literature and therefore appear in a recently proposed model [10]. This research takes a different view and suggests that factors like these have no relevance to modern students who are brought up in the technological age. The idea is to determine whether a model of technology acceptance and adoption can be proposed without these frequently studied factors and this is the primary motivation for this research.

1.1 Technology acceptance for e-learning

The technology acceptance model initially proposed by Davis has been a well-known entity to explain how human attitude and behavior predicts use of technology in presence of other external variables [11]. The technology here being technology based learning systems, a number of additional variables need consideration. Variables like cognitive, social and personal characteristics of learners play a vital part in design and employment of systems that are technology-based [12]. Therefore, it follows that technology acceptance is influenced by a number of factors that need exploration. In

this regard, TAM provided two key beliefs; perceived usefulness and perceived ease of use which explain the use of a technology system after being influenced by user's attitude and behavioral intention (BI). First, perceived usefulness (PU) is the degree to which a learner believes using technology will increase his or her learning. Secondly, perceived ease of use (PEOU) relates to the belief that technology based learning will be free of intellectual effort [13]. The application of TAM has been explored in the educational field also to determine how student's PU and PEOU affect their acceptance of e-learning initiatives [14][15].

1.2 External factors for technology acceptance

Many external factors affecting behavioral intention and use of technology were proposed in various studies. User-friendly course websites for e-learning are beneficial as website credibility, perceived ease of use and usefulness were found significant for student acceptance and satisfaction in courses involving websites [16]. A generalized TAM based upon five external factors was proposed after analyzing that self-efficacy, subjective norm, experience, computer anxiety and enjoyment were the most common external factors on TAM [17]. In another study, application of TAM to e-learning acceptance proposed that PU, PEOU and SN were predicting BI [18]. In the same study, PU was being predicted by PEOU, SN and job relevance while PEOU was predicted by computer self-efficacy, perceptions of external control, computer anxiety, and perceived enjoyment.

1.3 Research gaps and motivation

The topic of e-learning systems adoption based upon the TAM model has not been studied extensively in developing country like Pakistan. One related study conducted in Pakistan takes into account "student readiness" as the single student related external factor in the proposed model [19]. Moreover, studies on TAM based models have been based upon meta-analysis and generally taken into account external factors that were extensively studied in literature [17]. However, widely used factors like computer anxiety and experience make little sense with students from modern times since they have grown up with technology. This study takes a different view and proposes a model for e-learning systems adoption without these extensively studied constructs from past researches. The idea behind our proposed model is simple and intuitive. Students will adopt e-learning systems if they are able to find them enjoyable and see tangible benefits by using them to fulfill their academic needs.

1.4 Research objectives

The aim of this study is to present a simplified model of e-learning system adoption based upon the technology acceptance model (TAM) and to study the relationships between perceived usefulness and perceived ease of use of the e-learning system in presence of external factors like self-efficacy, enjoyment and results demonstrability. After a review of the relevant literature, a simple model is proposed to study behavioral

intention of students towards adoption of e-learning systems by students. The hypothesized relationships are explored and subsequent conclusions are highlighted based upon analysis of the data and research findings.

2 Theoretical Model and Hypotheses

This study proposes a model which is based upon the technology acceptance model providing a relationship between three major constructs; perceived ease of use (PEOU), perceived usefulness (PU) and behavioral intention (BI) of using an e-learning system. Figure 1 shows the proposed model which adds three external variables to the TAM. Two of these variables, enjoyment (ENJ) and result demonstrability (RES) are proposed as antecedents of PU. Self-efficacy (SE) is proposed as an antecedent to PEOU. These are briefly explained as follows

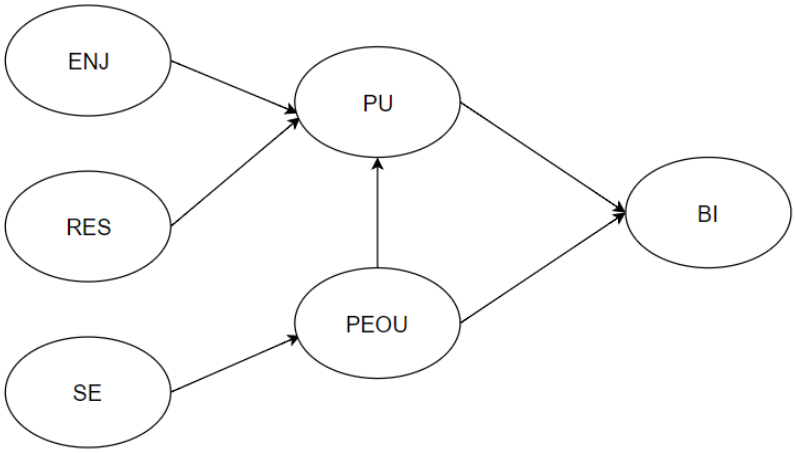

Fig. 1. Proposed Research Model

2.1 Enjoyment (ENJ)

Enjoyment in the context of technology-based systems relates to the activity of using these systems and finding them enjoyable [15]. Multiple studies involving research on multimedia e-learning systems, web based training and learning systems have found strong positive connection between enjoyment and perceived usefulness of these learning systems so it increases student's intention to use these systems [18][20][21]. Furthermore, a significant positive relationship was found between enjoyment and PU in 100 percent of the studies explored to propose an extended model based upon TAM [10]. Therefore, this external variable was considered a strong candidate for inclusion in the proposed model of this study.

2.2 Result demonstrability (RES)

A technological system is deemed useful when positive results and tangible benefits are seen by using these systems. This factor labeled as result demonstrability is defined as the tangibility of the result by using the innovation [22]. This construct was included in the extended technology acceptance model for the same reason of user's positive attitude towards these systems [23]. Many studies included result demonstrability as an external variable and reported its positive impact on perceived usefulness [18][24][25].

2.3 Self-efficacy (SE)

Self-efficacy has been used as a common external factor of TAM. Computer Self-Efficacy (CSE) is defined as one's ability to complete a particular task using a computer [26]. Computer literacy and computer anxiety are related in the sense that they can affect self-efficacy. People who consider computers too complex will avoid using them [27]. This suggests that students who have higher e-learning self-efficacy are more likely to use e-learning and computer supported education [28][29].

2.4 Research hypotheses

Having established the rationale of including the external variables in proposed model, the following hypotheses are being suggested for further evaluation.

H1: There is a positive relationship between PEOU and PU of the e-learning system

H2: There is a positive relationship between PU and BI of using the e-learning system

H3: There is a positive relationship between PEOU and BI of using the e-learning system

H4: SE of students is positively related to PEOU of the e-learning system

H5: ENJ is positively related to PU of the e-learning system

H6: RES is positively related to PU of the e-learning system

3 Methodology

The quantitative research approach with a cross-sectional design has been used in this research study to explore the proposed associations hypothesized between model constructs. Further details about the research instrument, sampling and data collection is provided in subsequent paragraphs.

3.1 Research instrument

The research instrument used for this study had two sections. First section of the questionnaire required the demographic details of participants and their e-learning utilization experience beyond the regular classroom. The second section aimed at gathering data about the six constructs of the research model namely PU, PEOU, ENJ,

RES, SE and BI. A summary of these constructs and corresponding references is provided in Table 1. Each of the six constructs used in research model has multiple items measured using five-point Likert scale ranging from strongly disagree to strongly agree.

3.2 Sample

The respondents of this research study are from the undergraduate programs of the faculty of engineering from four universities in Islamabad region. Out of the collected 377 responses, 19 were rejected due to missing data and unengaged responses to the questions. Finally, 358 responses were considered valid for further analysis.

Table 1. A summary of model constructs

Construct	No of items	Brief explanation	Ref
PU	4	Usefulness of a system to enhance individual performance	[11]
PEOU	4	Degree of difficulty or easy/effortless utilization of using a system	[11]
ENJ	3	Pleasure and inherent satisfaction derived from using technology	[32]
RES	3	Recognizable results of using the innovation	[23]
BI	3	Likelihood that a person plans to perform or not perform some specified behavior	[23]
SE	3	Ability or capacity to perform a task	[9]

The approach used for research constituted two steps where the measurement model was first validated by using confirmatory factor analysis (CFA), after which a structural model and path analysis was undertaken to explore the relationships between the constructs in order to perform hypothesis testing. The software used for statistical analysis were IBM SPSS version 24 and AMOS version 24.

3.3 Demographic summary

A typical undergraduate student in the sample is between 19 and 21 years old. As far as the gender distribution is concerned, there are 76.5 percent males and 23.5 percent females in the sample. These students asserted to have used e-learning systems in addition to their regular classroom studies and 67.6 percent stated that they used e-learning systems for up to an hour every day while 5.6 percent stated that they used it for more than 3 hours every day. The remaining 26.8 percent students used it for between 1 and 3 hours every day. Learning using YouTube videos and from relevant course material shared by other universities at websites like Coursera were the most common sources accessed by students.

4 Results

This section presents the results of statistical analysis conducted for hypothesis testing. Prior to the statistical analysis of collected data, assumptions of linearity and

normality were established. Reliability and validity checks of the scale were conducted. Subsequent paras present the analysis results of the measurement model and structural model. Results of hypothesis testing are provided next.

4.1 Measurement model

The measurement model was tested using AMOS 24 software by conducting CFA using maximum likelihood estimates. Construct validity was demonstrated by evaluating convergent and discriminant validity. For convergent validity, it is to be tested that measures that need to be related are in fact related. In order to establish convergent validity, composite reliability (CR) values should be greater than 0.70 and average variance extracted (AVE) values should be greater than 0.50 [30].

Table 2. Convergent and discriminant validity of model constructs

Var	CR	AVE	PU	PEOU	ENJ	RES	BI	SE	Cronbach alpha
PU	0.89	0.66	**0.81**						0.883
PEOU	0.88	0.65	0.46	**0.81**					0.870
ENJ	0.88	0.71	0.44	0.28	**0.84**				0.880
RES	0.86	0.67	0.48	0.35	0.53	**0.82**			0.856
BI	0.85	0.66	0.45	0.43	0.38	0.44	**0.81**		0.829
SE	0.79	0.57	0.48	0.75	0.27	0.28	0.46	**0.75**	0.794

Table 2 shows that CR values are all above 0.796 and AVE values are all above 0.567 indicating that all constructs have no issues related to reliability and convergent validity. Discriminant validity requires that measures that should not be related are in fact not related. This holds when the square root of AVE of a construct is higher than correlation values between that and all other constructs. From Table 2, it can be seen that all correlation values between the constructs are lower than square root of the AVE (values on the diagonal in bold), thereby establishing discriminant validity.

Measurement model was evaluated by calculating model fit measures using Amos 24 software. Model fit indices given in Table 3 were found within the required threshold values [31]. These results indicated that the proposed theoretical model was a good fit with observed data gathered through the survey.

4.2 Structural model

Assessment of the hypothesized relationships was performed next after evaluation of the measurement model. The standardized coefficients are reported in Table 4 which were all found significant at the $p<0.001$ level.

Table 3. Model goodness of fit measures

Measure	Estimate Measurement Model	Estimate Structural Model	Threshold
CMIN	280.98	325.586	--
DF	155	161	--
CMIN/DF	1.813	2.022	Between 1 and 3
CFI	0.969	0.959	>0.95
SRMR	0.052	0.071	<0.08
RMSEA	0.048	0.054	<0.06
PClose	0.654	0.238	>0.05

Results of the structural model are presented in Fig 2 indicating that all six hypotheses were supported by the data.

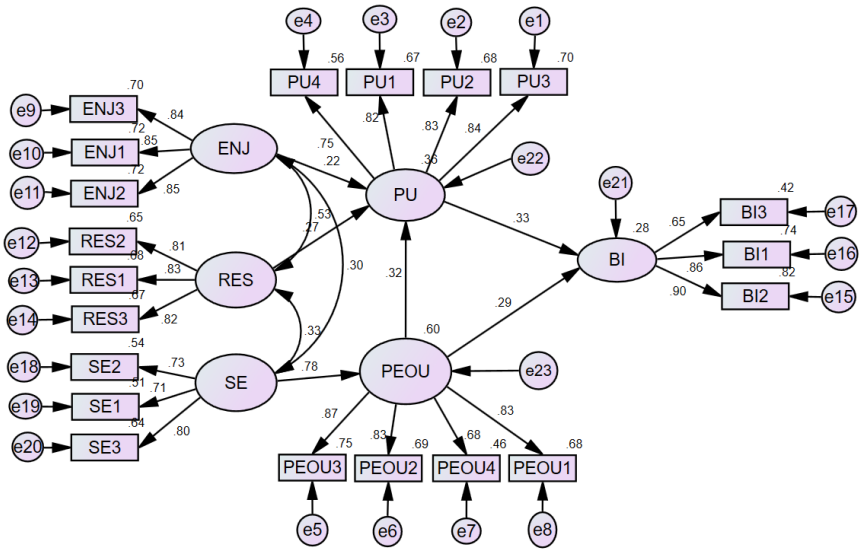

Fig. 2. Structural Model with Parameter Estimates

The first hypothesis suggested that perceived ease of use (PEOU) had a positive influence on perceived usefulness (PU) of the e-learning system as the standardized regression estimate of 0.345 was significant at the p<.001 level. The second and third hypotheses pertain to behavioral intention (BI) which is the key endogenous construct of this study. These hypotheses suggested that there was a positive influence of both PEOU and PU on the behavioral intention (BI) of using the e-learning system. Both hypotheses were supported as the standardized regression estimates of 0.323 and 0.294 were found significant at the p<.001 level. The fourth hypothesis suggested a positive influence of self-efficacy (SE) on PEOU of the e-learning system as the standardized regression weight was 0.762 and found significant. This also happens to be the estimate with largest magnitude found in the model indicating a strong influence of SE on PEOU.

The last two hypotheses suggest a positive influence of enjoyment (ENJ) and result demonstrability (RES) on PU of the e-learning system. The standardized regression weights for these are 0.226 and 0.276 respectively and significant at the p<.001 level. Moreover, considering the direct relationship of studied constructs with BI for using the e-learning system, PU construct had the highest influence on BI.

Table 4. Standardized path estimates

Hypothesis	Path	Estimate	t-value	p	Result
H1	PEOU → PU	.320	5.919	***	Supported
H2	PU → BI	.327	5.336	***	Supported
H3	PEOU → BI	.295	4.875	***	Supported
H4	SE → PEOU	.775	11.765	***	Supported
H5	ENJ → PU	.220	3.467	***	Supported
H6	RES → PU	.269	4.112	***	Supported
Note: *** $p < .001$					

5 Discussion

Access to e-learning systems is easier than before due to widespread availability of ubiquitous tools for connectivity owing to availability of mobile technologies. Increase in internet and smartphone usage to access learning content by the young generation has provided an emerging mode of mobile based learning in universities. The primary objective of this study was to determine the factors that elucidate relationship between behavioral intention of using e-learning platforms in education as explained by their perceived ease of use and usefulness. The results of the proposed model provided in this research support the conclusion that it is an adequate representation of the collected data and will help understand the behavioral intention of using e-learning systems.

The key contribution of this research is a simplified version of the technology acceptance model which re-establishes significant relationships among the original TAM constructs. The proposed model explains the behavioral intention of adopting e-learning platforms in a developing country like Pakistan where this has not been researched in prior studies. The first three hypotheses are supported thereby indicating that behavioral intention of using an e- learning system is dependent upon the two most important constructs (PU and PEOU) of TAM. This finding is consistent with many published researches in existing literature [18][21][23]. This indicates that the importance of adopting e-learning systems or portfolios for student learning and development is significant [33]. This finding suggests that students will adopt an e-learning system or portfolio if they are intrinsically motivated and think it will be useful in supporting them to collaborate and engage with the course and they are not likely to put in efforts to adopt a system which does not fulfill this need.

This study hypothesized that self-efficacy had a positive influence on perceived ease of use and the data supports this strongly. As expected, students with higher levels of computer self-efficacy and related skills will be more willing and at ease to adopt an e-learning system for supplementing course activities. This finding is also consistent with previous studies [17][18]. Since self-efficacy is like an intrinsic motivational factor, it

will facilitate an active learning process by motivating students to adopt e-portfolios for education. Moreover, this places a requirement on academic departments to provide requisite infrastructure and training to students early in the programs to make them self-sufficient in using technology-based systems in advanced stages of their education.

Lastly, significant relationships between results demonstrability and perceived usefulness, and between enjoyment and perceived usefulness have been found and these are also supported by previous work [18][25]. These findings were anticipated as students are more likely to spend their time on activities and enjoy doing those when it brings a positive change towards their studies. Asynchronous approach to instruction delivery using technology has been shown as effective in bringing about a positive approach towards students' achievement and helps stimulate their involvement in learning at their own pace. Recent studies [[34][35] have suggested similar benefits of using e-learning systems in education. In this case, using an e-learning system is considered useful as students can understand and demonstrate the positive results of using it for their benefit. Moreover, with the decreasing costs of many varieties of smart-phones and availability of mobile internet at reduced cost in Pakistan, students have an option of using mobile applications and accessing e-learning content at their convenience and they exercise this option regularly. Other potential benefits include cost effectiveness and environment friendly aspects of e-learning as compared to attending costly campus-based training programs at far locations.

As highlighted earlier, this study did not make use of some extensively studied external factors like computer anxiety and experience since these are not considered relevant to modern students. Therefore, the presented simplified model based upon TAM is considered a key step towards identification of external factors relevant to modern students and building upon those identified factors to explain adoption of e-learning systems in higher education institutions.

6 Conclusion and Future Work

The factors influencing adoption of e-learning systems were presented in the light of technology acceptance model in this research. This study provides evidence for e-education adoption in Pakistan as prior research did not exist in this context. The research model prepared as a result of data collected from n=358 students shows that they are likely to use the e-learning system for fulfilling their academic needs when they see its positive results. Students brought up in the digital age are familiar in use of computers since childhood and extensively use online learning resources in Pakistani universities. Every student owns a smartphone and this is making e-learning systems convenient to use for collaborative learning. Hence, computer anxiety and experience is not an issue with these students. Motivation by faculty is an important factor to bring about enjoyable student engagement by utilizing and exploring new learning opportunities. Investment in relevant technical infrastructure by universities is essential for successful integration of e-learning in academic programs.

A limitation of the study is the sample of students from four universities only and may limit the boundaries of generalizing the drawn conclusions from the analyzed data.

Moreover, additional dimensions could be added in future research to explain student behavioral intention and participation. For example, attitude towards learning technologies and personal characteristics of learners are some dimensions that can be explored to explain student participation.

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8 Authors

Aamer Hanif is working as Assistant Professor in the School of Management at Air University, Islamabad, Pakistan. His research interests include data mining and business analytics, project management and technology enhanced learning.

Ahmed F. Siddiqi is working as a Professor in Business School of the University of Central Punjab, Lahore, Pakistan. His research interests include data modeling and business analytics. He can be reached at dr.ahmedsiddiqi@ucp.edu.pk

Zunera Jalil is a faculty member at the Air University Islamabad in the Department of Computer Science. She is also associated with the National Center for Cyber

Security, Pakistan. Her research interests include information processing, computer forensics and intelligent systems. She can be reached at zunera.jalil@mail.au.edu.pk

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