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Extending the Technology Acceptance Model for Use of e-Learning Systems by Digital Learners

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ABSTRACT Technology-based learning systems enable enhanced student learning in higher-education institutions. This paper evaluates the factors affecting behavioral intention of students toward using e-learning systems in universities to augment classroom learning. Based on the technology acceptance model, this paper proposes six external factors that influence the behavioral intention of students toward use of e-learning. A quantitative approach involving structural equation modeling is adopted, and research data collected from 437 undergraduate students enrolled in three academic programs is used for analysis. Results indicate that subjective norm, perception of external control, system accessibility, enjoyment, and result demonstrability have a significant positive influence on perceived usefulness and on perceived ease of use of the e-learning system. This paper also examines the relevance of some previously used external variables, e.g., self-efficacy, experience, and computer anxiety, for present-world students who have been brought up as digital learners and have higher levels of computer literacy and experience.

INDEX TERMS e-learning, technology-acceptance model, technology-based learning, digital learners, behavioral intention.

I. INTRODUCTION

Owing to the internet and mobile-based multimedia communication technologies, students today have a multitude of opportunities to learn from the same material usually taught in classrooms and requiring physical presence. In a developing country like Pakistan, novel technologies are providing new ways for students to engage in learning activities and enabling them to use these for educational purposes thereby augmenting student learning in addition to regular classroom education. The value of technology in education for preparing engaging lectures, particularly by using Information and Communication Technology (ICT) tools for collaborative work and adopting self-regulated strategies has a positive impact on course effectiveness for students [1].

Handheld smart devices are common nowadays. They allow students to keep in touch with course materials and explore additional resources for learning. Peer interaction using Web 2.0 tools enables students to undertake real-time discussions, learn from mistakes, synchronize their thoughts, and motivates them to use internet resources with the end result of an enriched learning experience [2]. The availability of e-learning systems such as Blackboard and Google Classroom allow the integration of instructional materials, assessment modules, collaboration tools, and these systems have become a key constituent of instruction delivery in the university system [3]-[5]. Advantages gained with e-learning systems in education provide quick access to course materials and information, communication, collaboration, and many different ways to learn based on student needs. As new technological innovations keep surfacing, their applications in higher education pave the way for additional research. However, the primary objective of the adoption of new technologies and studies on exploring their enabling factors are always important. Accordingly, the issue of implementing technology-based instruction as a norm or standard practice in universities becomes a question of technology acceptance as to what motivates students to accept and use new technology for learning. However, students of present times have grown up with technology around them and are called digital natives because they handle technology in a natural way [6]. These digital learners have peculiar characteristics such as preference for a technology-infused learning environment with flexible schedule, need for collaborative learning with immediate feedback, and learning through activity with a

strong inclination toward the use of mobile devices and social networks [7]. Therefore, the question of technology acceptance by digital natives or learners requires the incorporation of a host of individually related influential factors relevant to this generation of technology.

The objectives of this research study are to develop and present a model of e-learning system adoption based on the technology-acceptance model (TAM) and subsequent research experiences gathered from different variants of the model. We explore and develop relationships between the perceived usefulness (PU) and perceived ease of use (PEOU) of the e-learning system in the presence of certain influencing factors, including learners' self-efficacy, enjoyment, perception of external control, subjective norm, result demonstrability and system accessibility. After a review of the literature relevant to these internal and external variables, an extension to the TAM model is proposed to study the behavioral intention (BI) of students toward the adoption of e-learning systems by students. The hypothesized relationships are analyzed and conclusions are drawn based on the findings.

To the best of our knowledge, research that links technology acceptance behavior with characteristics of digital natives or learners is lacking. Although many previous studies have explored and extended TAM, it has primarily been used on the basis of frequently occurring external variables in literature [8]. Hence, some of these studies have reported insignificant relationships between external variables and the use of technology considering that the proposed models have been tested on samples comprising digital natives [9]. These facts provide the motivation for this research and highlight a need for re-investigating external factors and relationships among TAM variables. Our research contribution culminates in an extended TAM in which external factors relevant to digital natives are proposed. Frequently studied external factors in the past such as computer anxiety, experience, and self-efficacy are questioned for relevance to digital natives, resulting in our proposed model that has better explanatory power compared with previous models wherein these variables were included. Moreover, the external factor of attitude toward using technology was initially removed from TAM and its successor models because of its nonsignificant effects on TAM relationships. However, attitude toward technology has been reinstated in our proposed model with noteworthy research findings.

This paper is organized as follows. The next section introduces the work related to various models and theories of technology acceptance. An overview of technology acceptance specifically for learning in higher education institutes is described in Section III. Section IV gives an account of the external variables and presents the proposed extended model for technology acceptance for e-learning systems. Section V mentions the research methodology, and Section VI provides the results of the measurement and structural models. Section VII discusses the results, and Section VIII concludes the paper with implications of the research.

II. RELATED WORK

Rapid advancements in ICT are resulting in the massive integration of smartphone applications and social networks into the personal and professional lives of users of these technologies. With the development of technology, various models for technology-acceptance behaviors started to emerge. Users' acceptance of these technologies and resulting models and theories of technology acceptance have been widely explored [10]–[13]. Table 1 provides a summary of various models that have been proposed in literature. The external factors proposed and considered significant in influencing BI to use technology systems are also provided. Most of these models are targeted toward the use of information systems in various contexts and indicate the importance of research on BI to use these systems.

TABLE 1. Models and theories of technology acceptance.

Model / Theory	External Factors	Ref
Theory of Reasoned Action	Attitude, Subjective norm	[14]
Technology- Acceptance Model	Perceived ease of use, Perceived usefulness	[15]
Theory of Planned Behavior	Attitude, Subjective norm, Perceived behavioral control	[16]
Model of PC Utilization	Complexity, Facilitating conditions, Social factors, Job fit, Long-term consequences	[17]
Innovation Diffusion Theory	Relative advantage, Complexity, Compatibility, Trialability, Observability	[18]
TAM-2	Subjective norm, Job relevance, Result demonstrability, Image, Output quality	[19]
Unified Theory of Acceptance and Use of Technology (UTAUT)	Performance and effort expectancy, Social influence, facilitating conditions	[20]
TAM-3	Factors of TAM-2 and Self- efficacy, Anxiety, Enjoyment, Usability, External control, Computer playfulness	[21]
UTAUT-2	Factors of UTAUT and Motivation, Price value, Habit	[22]
GETAMEL	Self-efficacy, Subjective norm, Enjoyment, Computer anxiety, Computer Experience	[8]

The development of new theoretical research frameworks have mostly relied on TAM and its variants as it became the most widely studied model. This model is supported by abundant empirical data collected and analyzed in various contexts. The key variables frequently used in the mentioned models can be identified as PU (performance expectancy), PEOU (effort expectancy), subjective norm (social influence), enjoyment, and attitude toward the use of technology. The next section discusses the application of TAM to the acceptance of e-learning systems in higher education.

III. TECHNOLOGY ACCEPTANCE FOR LEARNING

The TAM initially proposed by Davis is a well-known entity for explaining how human attitude and behavior predict the use of technology in the presence of other external variables [15]. For technology-based learning systems, a number of additional variables require consideration. These variables include the cognitive, social, and personal characteristics of learners, and these characteristics play vital roles in the design and employment of these systems [23]. Thus, technology acceptance is influenced by a number of factors requiring exploration. In this regard, TAM provides two key beliefs, namely, PU and PEOU that explain the use of a technology system after being influenced by user attitude (ATT) and BI. First, PU is the degree to which a learner believes using technology increases his or her learning. Second, PEOU is related to the belief that technology based learning is free of intellectual effort [15]. TAM application has been extensively explored in the higher education context to determine how students PU and PEOU affect their acceptance of e-learning initiatives [24]–[27].

TAM was used to study e-learning acceptance in Saudi Arabia, and PU, PEOU, and subjective norm (SN) are observed to predict BI [28]. In the same study, PU was predicted by PEOU, subjective norm, and job relevance, whereas PEOU was predicted by computer self-efficacy, perceptions of external control, computer anxiety, and perceived enjoyment. Many external factors affecting BI and the use of technology have been previously proposed. The most recent addition to the TAM family is the generalized TAM (GETAMEL) based on five external factors proposed after analyzing 107 research studies from the past 10 years exploring different external variables on the subject [8]. GETAMEL incorporates self-efficacy (SE), subjective norm (SN), experience (EXP), computer anxiety (CA), and enjoyment (ENJ) as the five most common external factors affecting technology acceptance for e-learning. GETAMEL has been tested and validated for e-portfolios used by students, and the external variables CA and EXP are not found to have a significant relationship with PU and PEOU contrary to past findings [9]. All these findings provide a rationale for the present research, enabling our key motivation for dropping these two constructs and exploring additional variables that can explain the BI of using e-learning systems by digital natives.

The topic of e-learning system adoption with regard to TAM is rarely studied in developing countries such as Pakistan. Only one related study conducted in Pakistan considers "student readiness" as the single student-related external factor in the proposed model [29]. In spite of being a developing country, Pakistan has sufficient internet penetration with over half of its population comprising of mobile phone users. The younger generation and university students among the population are extensive users of social networks. Hence, the present study attempts to establish a model that has been validated in the context of a developing country and is deemed applicable to other countries as well with similar technology related characteristics. This study proposes an extended model based on TAM by providing a relationship among three major constructs, namely, the PEOU, PU, and BI of using an e-learning system. Although variable ATT was initially a part of the TAM, it was removed because of the weak role between PU and ATT. The argument was that users without a positive attitude can still use a technology if its perceived benefits were visible [15]. The ATT construct was not included in the GETAMEL model for similar reasons [9]. However, we decided to include attitude in our model to test student attitude toward e-learning systems and to determine the strength of this construct in our local higher education context. Fig. 1 depicts the proposed model that extends TAM by adding six external variables and attitude construct to the model. The rationale for their inclusion is described below:

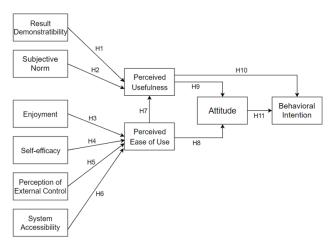


FIGURE 1. An extended technology acceptance model for e-learning. Hypothesized relationships are indicated.

A. RESULT DEMONSTRABILITY (RES)

A positive attitude about a system's usefulness is seen when the use of that system produces positive results for the user. This factor is denoted as result demonstrability and is defined as the tangibility of outcome of using the innovation [30]. This construct has been included in TAM-2, and user perceptions of result demonstrability have been found significant [19]. Subsequent studies have included result demonstrability as an external variable and reported its positive influence on PU [28], [31]–[34]. Students tend to accept entities that can produce positive results for them, therefore, we included this variable in the proposed model. The following hypothesis is stated for testing.

[H1] A positive relationship exists between RES and the PU of an e-learning system.

B. SUBJECTIVE NORM (SN)

Subjective Norm is about influencing a person's perception or thinking by people close to him regarding the performance of a certain behavior [20]. This factor is part of the theory of planned behavior, TAM-2, and UTAUT models, as evident in Table 1. In the case of e-learning, it is about how a student's inclination to use e-learning is influenced by the opinions of friends and faculty members in an educational context. Subjective norm can be the extent to which a student feels the environment and peer pressure to practice e-learning [35]. People who are valued commonly influence a person in real life; likewise, if beliefs can be used as an argument in favor of e-learning adoption, then a student would definitely give importance to such beliefs and render them useful for adoption. Subjective norm then acts like an intrinsic motivator to influence students to use e-learning [36]. A student is more likely to develop affirmative beliefs about technology-based learning and its applications in real life if he or she would be positively influenced by those close to him or her. Considering that peer and instructor influences exist in local culture, SN is included in the model and the following hypothesis is proposed.

[H2] A positive relationship exists between SN and the PU of an e-learning system.

C. ENJOYMENT (ENJ)

Enjoyment in the context of technology-based systems is related to the activity of using these systems and perceiving them to be agreeable and pleasing on their own [25]. Multiple studies involving research on multimedia e-learning systems, web-based training, and learning systems have shown a strong positive relationship between the enjoyment and PU of these learning systems, thereby increasing students' intention to use these systems [28], [37]–[40]. Moreover, a significant positive relationship has been found between enjoyment and PU in 100% of studies proposing the GETAMEL model [8]. Thus, this external variable is considered a strong candidate for inclusion in the hypothesized model of this study, and the following hypothesis is proposed.

[H3] A positive relationship exists between ENJ and the PEOU of an e-learning system.

D. SELF-EFFICACY (SE)

Self-efficacy is used as a common external factor of TAM in a large number of studies. Computer self-efficacy (CSE) is defined as one's belief about his/her ability to accomplish a particular task using a computer [41]. Computer literacy and computer anxiety are related in the sense that they can affect users' self-efficacy. Higher computer anxiety may result in poor performance and will negatively influence the use of computers because these are avoided by people who consider them too complex and believe that they cannot use them [42]. This finding suggests that students who have higher e-learning self-efficacy are more likely to use e-learning and computer-supported education [43]–[45]. Thus, the following hypothesis is proposed.

[H4] A positive relationship exists between SE and the PEOU of an e-learning system.

E. PERCEPTION OF EXTERNAL CONTROL (PEC)

External control is defined as the extent to which a person trusts that relevant technical resources exist in an organization to support system utilization for performing tasks [20]. PEC has been alternatively called facilitating conditions because complex systems require organizational support for their successful implementation. The same has been considered as an important external factor in previous research, leading to increased levels of user acceptance of new systems [19], [20], [46]. Moreover, during the development of TAM-3, PEC has been identified as a determinant of the PEOU of an e-learning system [21]. In a previous research on testing TAM-3 in Saudi Arabia to ascertain learner intentions of using the e-learning system, facilitating conditions or perceptions of external control have been determined to have the strongest effect on the PEOU [28]. This finding suggests that the beliefs of an individual about the presence of necessary resources and technical or organizational support enable the use of the system. For these reasons, we decided to include this variable in the proposed model. The related hypothesis is stated as follows.

[H5] A positive relationship exists between PEC and the PEOU of an e-learning system.

F. SYSTEM ACCESSIBILITY (SYSACC)

System accessibility simply implies that an accessible system can be used more conveniently and frequently than a system that is inaccessible and provides barriers in its use [24]. Problems such as the unavailability of appropriate technical infrastructure and slow speed internet connections hinder system accessibility. Students tend not to use online learning materials when issues of network connection, internet speed, and access reliability exist [47], [48]. Accordingly, these technical aspects of accessibility become critical success factors that determine the usability of an online-learning system. System accessibility has been considered as a significant external factor in other studies that had based their research model on TAM to predict the adoption and use of e-learning systems [24], [36], [49], [50]. Given that poorly accessible systems may not be usable even in the presence of favorable attitude and intention to use, this variable is included in the proposed model along with the following hypothesis to be tested.

[H6] A positive relationship exists between SYSACC and the PEOU of an e-learning system.

G. ADDITIONAL HYPOTHESES

Apart from the six external variables discussed earlier, additional paths exist between the key constructs of TAM (Fig. 1), which need to be tested for significance after the inclusion of these external variables. Thus, the following five additional hypotheses are proposed.

[H7] A positive relationship exists between the PEOU and PU of an e-learning system.

[H8] A positive relationship exists between the PEOU of and ATT toward an e-learning system.

[H9] A positive relationship exists between the PU of and ATT toward an e-learning system.

[H10] A positive relationship exists between the PU of and BI toward an e-learning system.

[H11] A positive relationship exists between the ATT and BI toward an e-learning system.

V. RESEARCH METHODOLOGY

This study used a quantitative approach with a cross-sectional design to investigate the relationships among the constructs of the proposed research model. The development of research instruments involved 10 constructs adapted from previously validated instruments used in similar contexts. Table 2 contains references to previous research from where the questionnaire items for each of these constructs were adopted. Each construct had multiple items measured using the five-point Likert scale ranging from (1) strongly disagree to (5) strongly agree.

TABLE 2. Convergent validity and reliability of constructs.

	Mean (SD)	CR	AVE	Cronbach's Alpha	Items in scale	Ref
PU	4.05 (0.70)	0.875	0.637	0.874	4	[15, 19]
PEOU	3.63 (0.77)	0.763	0.524	0.740	3	[15, 19]
ENJ	3.65 (0.76)	0.847	0.649	0.846	3	[53]
RES	3.88 (0.71)	0.791	0.558	0.792	3	[19]
BI	3.95 (0.72)	0.848	0.651	0.846	3	[19]
SYSACC	3.82 (0.78)	0.757	0.509	0.758	3	[25]
ATT	3.90 (0.77)	0.785	0.550	0.783	3	[54]
PEC	3.89 (0.71)	0.768	0.526	0.763	3	[53]
SN	4.10 (0.73)	0.813	0.592	0.807	3	[20]
SE	3.91 (0.69)	0.781	0.545	0.773	3	[36]

A. SAMPLING AND PROCEDURE

Data was collected from undergraduate students of twelve universities in the Islamabad/Rawalpindi region and divided into two strata (public and private sector institutions). Students studying computer science, management science, and engineering disciplines were included as these were the most common disciplines in undergraduate education in Pakistan. Demographic details of participants and their e-learning experiences were gathered in addition to information about constructs of the research model. The approach used for research constituted two steps. First, the measurement model was validated by confirmatory factor analysis (CFA). Second, a structural model and path analysis were used to explore the relationships among the constructs to perform hypothesis testing. The software used for statistical analysis were IBM SPSS version 24 and AMOS [51], [52]

B. DEMOGRAPHIC ANALYSIS

A total of 479 responses were collected. Among them, 437 were considered usable after thorough data screening, which included the removal of un-engaged responses and multivariate outliers. The sample consisted of 76% males and 24% females. About 87% of the students had their own PC/laptop. More than 50% of the students had computer experience of over 7 years, and only about 15% students had computer experience of less than 3 years. About 50% of the students stated that they used the internet for over 14 hours per week for learning activities. The most common way of learning outside the classroom was using YouTube videos and from related lectures of other universities offered at websites such as Coursera. From the demographic data, we concluded that these students were thoroughly experienced in using computers and the internet for learning purposes, and that computer anxiety was not an issue worth exploring in this sample.

VI. RESULTS AND ANALYSIS

This section reveals the analysis results. Assumptions of linearity and normality of constructs were established prior to the statistical analysis of collected data. Reliability and validity checks of the scale for dataset size N=437 were conducted. Analysis results of the measurement model, structural model and path analysis for the hypotheses developed for this study are presented as follows.

A. MEASUREMENT MODEL

The measurement model was tested using AMOS 24 software by conducting CFA with maximum likelihood estimates. Validity and reliability of the constructs were checked first. Composite reliability (CR) values should be >0.70, and average variance extracted (AVE) values should be >0.50 for convergent validity [55]. Reliability of the research instrument was determined by Cronbach's Alpha coefficient method and should be >0.70 for acceptability [56]. Table 2 shows that CR values are all >0.75 and AVE values are all >0.5, indicating that all constructs have no issues related to convergent validity and reliability of scale. Measurement model fit indices are provided in Table 3, in which a combination of absolute and incremental fit indices are shown. These are the most frequently reported indices in literature related to structural equation modeling (SEM) [56]. The model-fit indices given in Table 3 are found to be within the required

TABLE 3. Model fit measures.

Measure	Measurement model estimate	Structural model estimate	Threshold (cutoff point)
CMIN	708.19	842.27	-
DF	389	407	-
CMIN/DF	1.821	2.069	1 < CMIN/DF < 3
CFI	0.956	0.94	> 0.95
SRMR	0.042	0.052	< 0.08
RMSEA	0.043	0.050	< 0.06

threshold values [57]. These results indicate that the proposed theoretical model is a good fit with observed data gathered through the survey.

B. STRUCTURAL MODEL

The structural model attempted to identify dependence relationships among the model constructs, as the relationships are assigned from one construct to another based on the research model that has been proposed. A two-step approach was used to assess the structural model as suggested by [58]. First, goodness-of-fit (GOF) indices for the structural model are evaluated, after which standardized parameter estimates are used to justify the causal relationships and test the proposed hypotheses.

The first step requires testing of the overall model GOF and assessing it using a similar criterion as done for the

measurement model. Structural model GOF closer to measurement model-fit values are desirable and suggest a better fit. Table 3 provides model-fit indices for the hypothesized structural model.

The standardized coefficients are reported in Table 4, along with the results of hypothesis testing. The structural model with path coefficients are presented in Fig. 2. The fit indices for the hypothesized model suggest adequate fit as the GOF statistics for the model are well within the acceptable limits of a good model fit.

TABLE 4. Parameter estimates and results of hypotheses.

Hypothesis	Relationship	Estimate	Result
H1	$\text{RES} \rightarrow \text{PU}$	0.382 ***	Supported
H2	$\mathrm{SN} \to \mathrm{PU}$	0.281 **	Supported
Н3	$ENJ \rightarrow PEOU$	0.325 ***	Supported
H4	$SE \rightarrow PEOU$	0.028	Not Supported
H5	$PEC \rightarrow PEOU$	0.346 **	Supported
H6	$SYSACC \rightarrow PEOU$	0.211 ***	Supported
H7	$PEOU \rightarrow PU$	0.114	Not Supported
H8	$PEOU \rightarrow ATT$	1.061 ***	Supported
H9	$PU \rightarrow ATT$	0.105	Not Supported
H10	$PU \rightarrow BI$	0.339 ***	Supported
H11	$ATT \rightarrow BI$	0.546 ***	Supported

*** Significant at p < 0.001, Significant at p < 0.05

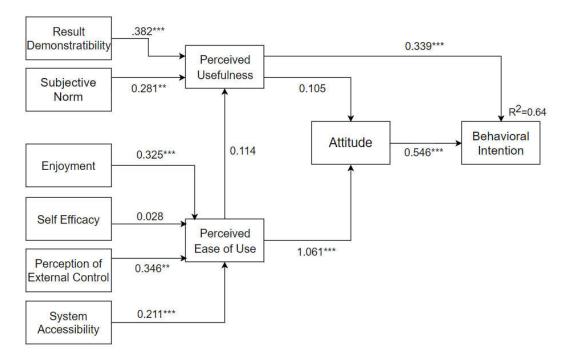


FIGURE 2. Structural model with path estimates.

Model	Chi-sq	df	CMIN/df	CFI	SRMR	RMSEA	AIC	BIC	R^2
Hypothesized	842.3	407	2.069	0.94	0.052	0.05	1020.3	1383.4	0.64
Model A	646.3	329	1.965	0.95	0.05	0.047	800.3	1114.5	0.63

 TABLE 5. Comparison of goodness of fit measures with competing model.

Note: AIC: Akaike Information criterion, BIC: Bayesian information criterion

C. COMPARISON WITH COMPETING MODEL

Based on the results of hypothesis testing, a competing model is considered for comparison purposes. The idea was to identify the effect of model relationships with the variable SE removed from the model. This model called Model-A contains all original constructs except for SE given the nonsignificant effect of SE on the PEOU. Model-fit measures for our proposed extended TAM and Model-A are provided in Table 5 for comparison.

Table 5 shows that the competing model with SE removed results in a better model as evident from model-fit measures. An interesting observation is that model R^2 dropped by 1% only in the model without SE, indicating negligible reduction in model explanatory power.

VII. DISCUSSION

This study aims to determine the relationship between proposed external factors and the BI toward using e-learning platforms in education as explained by their PU and PEOU. Table 4 shows support for most of the proposed hypotheses. The results of the proposed model's GOF measures confirm that the proposed model can adequately represent the collected data and help understand the BI of digital learners toward using e-learning systems. The significance of each of the model constructs as determined by hypothesis testing is then discussed.

RES had significant positive influence on PU as hypothesized, which was consistent with previous studies [28], [59], [60]. The tangibility of outcome or results of using e-learning systems seem to appear significant to undergraduate students who recognize that learning from internet resources can increase their learning and enables them to better understand the course material. This finding also suggests that digital learners tend to go for technological resources for learning when they can evidently benefit from these resources by investing their time in learning from their use.

The role of SN as an extrinsic motivational factor affecting student attitude and BI toward using e-learning has been previously established [9], [24], [28], [61]. Peers and instructors are in a position to shape and influence student perceptions to adopt e-learning systems. Moreover, social pressure and influence of important persons in one's life are prevalent factors in the Pakistani society, wherein individuals feel obliged to act upon or even change their behavior, opinion, and attitude under the influence of those who they feel are important in their lives.

The positive effect of ENJ on PEOU is consistent with many past reports [9], [37], [62], [63]. The reason for the significance of this construct is the relationship of the current habits of students to the extensive use of social networks and multimedia systems for communication. Hence, they also enjoy using these systems for learning at their own pace and in their own time because multimedia e-learning systems provide students with a gratifying learning experience. This experience increases their motivation to learn even outside the formal classroom setting.

SE does not have a significant relationship with the PEOU contrary to previous research findings [28], [44].

This finding is unexpected as it appears to contradict common belief that individuals with higher levels of computer SE are bound to be confident about their use of computer systems and can overcome any difficulty related to computer use. Some previous studies as highlighted by [8] have reported similar findings [35], [64], [65]. The most likely explanation of this inconsistency is the fact that students in these studies have higher levels of computer experience and efficacy. Results of the competing model without SE also indicate that this construct does not affect BI toward using technology. Students who are digital natives and proficient in using internet resources have a higher SE by default. Therefore, this construct does not contribute significantly as a determinant for the PEOU, neither does it significantly affect BI when removed from the model. However, these findings may be substantiated by undertaking additional research in diverse contexts and with different student experience levels with technology.

The PEC positively affects PEOU of the e-learning system. This construct is important as it relates to the availability of necessary technical infrastructure in the organization to support use of the system. Even if students strongly intend to use e-learning systems, their BI is affected by the strong or poor availability of the necessary technical and support features of the system. This finding is also consistent with past studies [21], [28], [60].

SYSACC has a positive effect on the PEOU of an e-learning system. This finding is consistent with past studies [66], [67]. With the advent of new technologies and learning opportunities available, system accessibility to learners also requires the availability of asynchronous communication between learners and instructors, discussion fora, evaluation mechanisms, and system-support mechanisms for students. The availability of mobile devices with students and the provision of Wi-Fi services in university campuses is significantly increasing easy and quick access to information.

PEOU does not have a significant relationship with PU contrary to previous findings [8], [9]. A recent study using GETAMEL to study e-learning adoption in Azerbaijan showed that PEOU had a non-significant effect on the

PU [68]. About 70% of the students in this study had computer and mobile related experience of over 3 years and were proficient in using technological resources for e-learning. In the present research, students are also experienced in the use of computers and the internet. Given that PEOU reflects how users assess their ease of use of e-learning and deals with the intrinsic motivational aspect of using information technology [69], students with higher experience levels of using computers have other reasons (e.g., enjoyment, and result demonstrability) to use e-learning systems. For these students or digital natives, using technology is a current way of life.

We observed that PEOU had a significant positive effect on ATT; however, the path from the PU to ATT was found to be non-significant. These findings are consistent with previous ones from studies involving the attitude construct [24], [70], [71]. Students finding e-learning systems easy to use have a favorable attitude toward using the system.

The PU is also found to have a significant positive affect on BI. This path has been found to be significant in many previous studies as it is one of the key paths in the original TAM and has been a part of many extended TAM-based models [8], [68], [70]. This finding shows that without any attitude formation, a system perceived useful can find a strong BI toward using it. Useful implications for educators can be providing assistance to learners and emphasizing the effectiveness and usefulness of e-learning systems to increase their usage. Moreover, information and training sessions can help students understand how they could improve their learning in academic courses by using online resources.

This research has found attitude to be a significant predictor of BI toward using e-learning. Some studies had removed ATT from the model because of its weak role between interconstruct relationships [40], [72]. However, the present study finds significant roles of the ATT construct, i.e., its effect on BI is greater than that of PU, consistent with previous studies [73], [74]. These findings suggest that a student's attitude is a strong predictor of BI toward using the system with the fact that students find this system easy to use. However, system usefulness does not affect student attitude toward it, thereby highlighting the importance of student attitude in Pakistani higher education. BI toward using the e-learning system is more strongly affected by positive attitude toward the system than by the usefulness of the system. Thus, students with a positive attitude toward e-learning systems are more likely to use them. Hence, course leaders and instructors need to shape student attitudes and improve their engagement and desirability to use the system apart from merely proving that the system is useful for their studies and learning.

The key contribution of this research is an adaptation of TAM that explains the BI toward using e-learning systems by adding attitude and eliminating experience and computer anxiety constructs, which do not apply to digital natives. The model explains 64% of the variation (\mathbb{R}^2) in the dependent variable (BI), which is greater than the 58% variation explained by GETAMEL [9]. Constructs like self-efficacy,

computer anxiety and experience, which are tested and found significant in other models such as GETAMEL, previously seem to be of little relevance with changed characteristics of students in the present age. Given that learning technologies keep evolving and newer ways to deliver learning content are bound to emerge, continuous research is required to update the TAM. The proposed model is a step in that direction and is expected to generate additional research in different contexts.

VIII. CONCLUSIONS AND IMPLICATIONS

The deployment and use of e-learning systems in Pakistani universities is increasing, and students are expected to use them in their courses. An extended TAM model for the adoption of technology for e-learning is proposed with factors considered relevant to digital learners in a developing country. Subjective norm, perception of external control, system accessibility, enjoyment, and result demonstrability have a significant positive influence on using e-learning systems. Learners' self-efficacy does not seem to influence the use of these systems by digital learners. Computer experience and anxiety are not relevant to digital natives. Students are likely to use the e-learning systems if they have complete access, can see tangible results of use, are socially influenced appropriately, and enjoy using these for a perceived benefit in fulfilling their academic needs. The role of "attitude" construct is re-established, and its importance is thus justified. This rationale explains the selection and testing of the external/behavioral variables in the proposed model.

The practical implications of this research are relevant to administration and faculty as well in addition to students. University administration can invest in relevant technical infrastructure to enable successful implementation of e-learning systems in academic programs. The use of mobile technologies is rendering e-learning systems convenient to use and promotes collaborative learning. Faculty can prepare course material and assignments to enable personal mobile devices to expand student engagement by exploring blended learning opportunities. Research on technology acceptance for e-learning in the Pakistani higher education context is lacking, and this study helps shape similar studies undertaken in other developing countries.

In the dynamic technical and academic learning scenarios, no model can be the ultimate explanation of ground reality. Hence, the present study is also limited in the sense that it can generate extensive results based on additional dimensions being added to explain student BI and participation. Further research can be undertaken to study other external factors in different contexts and cultures in developed countries as well. The mediating and moderating effects on the BI toward technology adoption also warrants further analysis to study user acceptance of e-learning.

REFERENCES

 V. Venkatesh, A.-M. Croteau, and J. Rabah, "Perceptions of effectiveness of instructional uses of technology in higher education in an era of Web 2.0," in *Proc. IEEE 47th Hawaii Int. Conf. Syst. Sci. (HICSS)*, Jan. 2014, pp. 110–119.

- [2] F.-T. Leow and M. Neo, "Redesigning for collaborative learning environment: Study on students' perception and interaction in Web 2.0 tools," *Procedia-Social Behav. Sci.*, vol. 176, pp. 186–193, Feb. 2015.
- [3] Y.-H. Lee, Y.-C. Hsieh, and Y.-H. Chen, "An investigation of employees' use of e-learning systems: Applying the technology acceptance model," *Behav. Inf. Technol.*, vol. 32, no. 2, pp. 173–189, 2013.
- [4] S. Bhat, R. Raju, A. Bikramjit, and R. D'Souza, "Leveraging E-learning through Google classroom: A usability study," *J. Eng. Educ. Transformations*, vol. 31, no. 3, pp. 129–135, 2018.
- [5] S.-C. Lin, S. F. Persada, and R. Nadlifatin, "A study of student behavior in accepting the blackboard learning system: A technology acceptance model (TAM) approach," in *Proc. IEEE 18th Int. Conf. Comput. Supported Cooperat. Work Design (CSCWD)*, May 2014, pp. 457–462.
- [6] M. Prensky, "Digital natives, digital immigrants part 1," *Horizon*, vol. 9, no. 5, pp. 1–6, 2001.
- [7] N. Sarkar, W. Ford, and C. Manzo, "Engaging digital natives through social learning," *Systemics, Cybern. Inform.*, vol. 15, no. 2, pp. 1–4, 2017.
- [8] F. Abdullah and R. Ward, "Developing a general extended technology acceptance model for E-learning (GETAMEL) by analysing commonly used external factors," *Comput. Human Behav.*, vol. 56, pp. 238–256, Mar. 2016.
- [9] F. Abdullah, R. Ward, and E. Ahmed, "Investigating the influence of the most commonly used external variables of TAM on students' perceived ease of use (PEOU) and perceived usefulness (PU) of e-portfolios," *Comput. Human Behav.*, vol. 63, pp. 75–90, Oct. 2016.
- [10] Y. H. Al-Mamary, M. Al-Nashmi, Y. A. G. Hassan, and A. Shamsuddin, "A critical review of models and theories in field of individual acceptance of technology," *Int. J. Hybrid Inf. Technol.*, vol. 9, no. 6, pp. 143–158, 2016.
- [11] W. Jen, T. Lu, and P.-T. Liu, "An integrated analysis of technology acceptance behaviour models: Comparison of three major models," *MIS REVIEW, Int. J.*, vol. 15, no. 1, pp. 89–121, 2009.
- [12] P. C. Lai, "The literature review of technology adoption models and theories for the novelty technology," J. Inf. Syst. Technol. Manage., vol. 14, no. 1, pp. 21–38, 2017.
- [13] M. Marangunić and A. Granić, "Technology acceptance model: A literature review from 1986 to 2013," *Universal Access Inf. Soc.*, vol. 14, no. 1, pp. 81–95, 2015.
- [14] M. Fishbein and I. Ajzen, Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research. Reading, MA, USA: Addison-Wesley, 1975.
- [15] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quart.*, vol. 13, no. 3, pp. 319–340, 1989.
- [16] I. Ajzen, "The theory of planned behavior," Org. Behav. Human Decision Process., vol. 50, no. 2, pp. 179–211, 1991.
- [17] R. L. Thompson, C. A. Higgins, and J. M. Howell, "Personal computing: Toward a conceptual model of utilization," *MIS Quart.*, vol. 15, no. 1, pp. 125–143, 1991.
- [18] E. M. Rogers, *Diffusion of Innovations*, 4th ed. New York, NY, USA: The Free Press, 1995.
- [19] V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," *Manage. Sci.*, vol. 46, no. 2, pp. 186–204, 2000.
- [20] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Quart.*, vol. 27, no. 3, pp. 425–478, 2003.
- [21] V. Venkatesh and H. Bala, "Technology acceptance model 3 and a research agenda on interventions," *Decision Sci.*, vol. 39, no. 2, pp. 273–315, 2008.
- [22] V. Venkatesh, J. Y. L. Thong, and X. Xu, "Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology," *MIS Quart.*, vol. 36, no. 1, pp. 157–178, 2012.
- [23] M. Siadaty and F. Taghiyareh, "E-learning: From a pedagogical perspective," Int. J. Inf. Sci. Manage., vol. 6, no. 2, pp. 99–117, 2012.
- [24] S. Y. Park, "An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-learning," *J. Educ. Technol. Soc.*, vol. 12, no. 3, pp. 150–162, 2009.
- [25] Y. Park, H. Son, and C. Kim, "Investigating the determinants of construction professionals' acceptance of Web-based training: An extension of the technology acceptance model," *Automat. Construction*, vol. 22, pp. 377–386, Mar. 2012.

- [26] A. M. Elkaseh, K. W. Wong, and C. C. Fung, "Perceived ease of use and perceived usefulness of social media for e-learning in Libyan higher education: A structural equation modeling analysis," *Int. J. Inf. Edu. Technol.*, vol. 6, no. 3, pp. 192–199, 2016.
- [27] S. K. Sharma, J. K. Chandel, and S. M. Govindaluri, "Students' acceptance and satisfaction of learning through course websites," *Educ., Bus. Soc., Contemp. Middle Eastern Issues*, vol. 7, nos. 2–3, pp. 152–166, 2013.
- [28] S. S. Al-Gahtani, "Empirical investigation of e-learning acceptance and assimilation: A structural equation model," *Appl. Comput. Inform.*, vol. 12, no. 1, pp. 27–50, 2016.
- [29] S. Iqbal and I. A. Qureshi, "M-learning adoption: A perspective from a developing country," *Int. Rev. Res. Open Distrib. Learn.*, vol. 13, no. 3, pp. 147–164, 2012.
- [30] G. C. Moore and I. Benbasat, "Development of an instrument to measure the perceptions of adopting an information technology innovation," *Inf. Syst. Res.*, vol. 2, no. 3, pp. 192–222, 1991.
- [31] P. E. Ramírez-Correa, J. Arenas-Gaitán, and F. J. Rondán-Cataluña, "Gender and acceptance of e-learning: A multi-group analysis based on a structural equation model among college students in chile and spain," *PLoS ONE*, vol. 10, no. 10, p. e0140460, 2015.
- [32] V. Lefievre, "Gender differences in acceptance by students of training software for office tools," presented at the 14th Annu. Int. Conf. Educ., 2012.
- [33] J. Arenas-Gaitán, F. J. Rondán-Cataluña, and P. E. Ramírez-Correa, "Gender influence in perception and adoption of e-learning platforms," in *Proc.* 9th WSEAS Int. Conf. Data Netw., Commun., Comput., 2010, pp. 30–35.
- [34] N. Zhang, X. Guo, and G. Chen, "IDT-TAM integrated model for IT adoption," *Tsinghua Sci. Technol.*, vol. 13, no. 3, pp. 306–311, 2008.
- [35] Á. F. Agudo-Peregrina, Á. Hernández-García, and F. J. Pascual-Miguel, "Behavioral intention, use behavior and the acceptance of electronic learning systems: Differences between higher education and lifelong learning," *Comput. Human Behav.*, vol. 34, pp. 301–314, May 2014.
- [36] S. Y. Park, M.-W. Nam, and S. B. Cha, "University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model," *Brit. J. Educ. Technol.*, vol. 43, no. 4, pp. 592–605, 2012.
- [37] H. Zare and S. Yazdanparast, "The causal Model of effective factors on intention to use of information technology among payamnoor and traditional universities students," *Life Sci. J.*, vol. 10, no. 2, pp. 46–50, 2013.
- [38] K. Praveena and S. Thomas, "Continuance intention to use facebook: A study of perceived enjoyment and TAM," *Bonfring Int. J. Ind. Eng. Manage. Sci.*, vol. 4, no. 1, pp. 24–29, 2014.
- [39] S. H.-P. Shyu and J.-H. Huang, "Elucidating usage of e-government learning: A perspective of the extended technology acceptance model," *Government Inf. Quart.*, vol. 28, no. 4, pp. 491–502, 2011.
- [40] Y.-C. Chen, Y.-C. Lin, R. C. Yeh, and S.-J. Lou, "Examining factors affecting college students' intention to use Web-based instruction systems: Towards an integrated model," *Turkish Online J. Educ. Technol.*, vol. 12, no. 2, pp. 111–121, 2013.
- [41] H. V. Kher, J. P. Downey, and E. Monk, "A longitudinal examination of computer self-efficacy change trajectories during training," *Comput. Human Behav.*, vol. 29, no. 4, pp. 1816–1824, 2013.
- [42] C.-L. Lee and M.-K. Huang, "The influence of computer literacy and computer anxiety on computer self-efficacy: The moderating effect of gender," *Cyberpsychology, Behav., Social Netw.*, vol. 17, no. 3, pp. 172–180, 2014.
- [43] V. Celik and E. Yesilyurt, "Attitudes to technology, perceived computer self-efficacy and computer anxiety as predictors of computer supported education," *Comput. Educ.*, vol. 60, no. 1, pp. 148–158, 2013.
- [44] C.-S. Chang, E. Z.-F. Liu, H.-Y. Sung, C.-H. Lin, N.-S. Chen, and S.-S. Cheng, "Effects of online college student's Internet self-efficacy on learning motivation and performance," *Innov. Educ. Teach. Int.*, vol. 51, no. 4, pp. 366–377, 2014.
- [45] N. Pellas, "The influence of computer self-efficacy, metacognitive selfregulation and self-esteem on student engagement in online learning programs: Evidence from the virtual world of second life," *Comput. Human Behav.*, vol. 35, pp. 157–170, Jun. 2014.
- [46] S. Taylor and P. A. Todd, "Understanding information technology usage: A test of competing models," *Inf. Syst. Res.*, vol. 6, no. 2, pp. 144–176, 1995.
- [47] M. A. Musa and M. S. Othman, "Critical success factor in e-learning: An examination of technology and student factors," *Int. J. Adv. Eng. Technol.*, vol. 3, no. 2, pp. 140–148, 2012.

- [48] W.-C. Poon, K. L.-T. Low, and D. G.-F. Yong, "A study of Web-based learning (WBL) environment in Malaysia," *Int. J. Educ. Manage.*, vol. 18, no. 6, pp. 374–385, 2004.
- [49] Y.-H. Lee, C. Hsiao, and S. H. Purnomo, "An empirical examination of individual and system characteristics on enhancing e-learning acceptance," *Australas. J. Educ. Technol.*, vol. 30, no. 5, pp. 562–579, 2014.
- [50] B. Wu and C. Zhang, "Empirical study on continuance intentions towards E-learning 2.0 systems," *Behav. Inf. Technol.*, vol. 33, no. 10, pp. 1027–1038, 2014.
- [51] J. Gaskin and J. Lim, Master Validity Tool, AMOS Plugin, 2nd ed. Gaskination's Statwiki, 2016. [Online]. Available: http://statwiki.kolobkreations.com/
- [52] J. Gaskin and J. Lim, Model fit Measures, AMOS Plugin, 2nd ed. Gaskination's Statwiki, 2017. [Online]. Available: http://statwiki.kolobkreations.com/
- [53] V. Venkatesh, "Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model," *Inf. Syst. Res.*, vol. 11, no. 4, pp. 342–365, 2000.
- [54] R. Cheung and D. Vogel, "Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for elearning," *Comput. Educ.*, vol. 63, pp. 160–175, Apr. 2013.
- [55] L. T. Hu and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," *Structural Equation Model.*, *Multidisciplinary J.*, vol. 6, no. 1, pp. 1–55, 1999.
- [56] J. F. Hair, Jr., W. C. Black, B. J. Babin, R. E. Anderson, and R. L. Tatham, *Multivariate Data Analysis*, vol. 6. Upper Saddle River, NJ, USA: Prentice-Hall, 2006.
- [57] J. B. Schreiber, A. Nora, F. K. Stage, E. A. Barlow, and J. King, "Reporting structural equation modeling and confirmatory factor analysis results: A review," *J. Educ. Res.*, vol. 99, no. 6, pp. 323–338, 2006.
- [58] E. W. L. Cheng, "SEM being more effective than multiple regression in parsimonious model testing for management development research," *J. Manage. Develop.*, vol. 20, no. 7, pp. 650–667, 2001.
- [59] N. P. Wingo, N. V. Ivankova, and J. A. Moss, "Faculty perceptions about teaching online: Exploring the literature using the technology acceptance model as an organizing framework," *Online Learn.*, vol. 21, no. 1, pp. 15–35, 2017.
- [60] M. Y. Yi, J. D. Jackson, J. S. Park, and J. C. Probst, "Understanding information technology acceptance by individual professionals: Toward an integrative view," *Inf. Manage.*, vol. 43, no. 3, pp. 350–363, 2006.
- [61] T.-H. Chu and Y.-Y. Chen, "With good we become good: Understanding e-learning adoption by theory of planned behavior and group influences," *Comput. Educ.*, vols. 92–93, pp. 37–52, Jan./Feb. 2016.
- [62] Y. S. Poong, S. Yamaguchi, and J.-I. Takada, "Investigating the drivers of mobile learning acceptance among young adults in the world heritage town of Luang Prabang, Laos," *Inf. Develop.*, vol. 33, no. 1, pp. 57–71, 2017.
- [63] A. S. Al-Adwan, A. Al-Madadha, and Z. Zvirzdinaite, "Modeling students' readiness to adopt mobile learning in higher education: An empirical study," *Int. Rev. Res. Open Distrib. Learn.*, vol. 19, no. 1, pp. 1–21, 2018.
- [64] S. H. Purnomo and Y.-H. Lee, "E-learning adoption in the banking workplace in Indonesia: An empirical study," Inf. Develop., vol. 29, no. 2, pp. 138–153, 2013.
- [65] M. Rezaei, H. M. Mohammadi, A. Asadi, and K. Kalantary, "Predicting e-learning application in agricultural higher education using technology acceptance model," *Turkish Online J. Distance Edu.*, vol. 98, no. 1, pp. 85–95, 2008.
- [66] R. Thomson, C. S. Fichten, A. Havel, J. Budd, and J. Asuncion, "Blending universal design, E-learning, and information and communication technologies," *Universal Design in Higher Education: From Principles to Practice.* Cambridge, MA, USA: Harvard Education Press, 2015, pp. 275–284.
- [67] W. S. Shin and M. Kang, "The use of a mobile learning management system at an online university and its effect on learning satisfaction and achievement," *Int. Rev. Res. Open Distrib. Learn.*, vol. 16, no. 3, pp. 110–130, 2015.
- [68] C.-T. Chang, J. Hajiyev, and C.-R. Su, "Examining the students' behavioral intention to use e-learning in Azerbaijan? The general extended technology acceptance model for E-learning approach," *Comput. Edu.*, vol. 111, pp. 128–143, Aug. 2017.
- [69] D. Gefen and D. W. Straub, "The relative importance of perceived ease of use in is adoption: A study of E-commerce adoption," J. Assoc. Inf. Syst., vol. 1, no. 1, pp. 1–28, 2000.

- [70] R. Boateng, A. S. Mbrokoh, L. Boateng, P. K. Senyo, and E. Ansong, "Determinants of e-learning adoption among students of developing countries," *Int. J. Inf. Learn. Technol.*, vol. 33, no. 4, pp. 248–262, 2016.
- [71] A. Meerza and G. Beauchamp, "Factors influencing undergraduates attitudes towards ICT: An empirical study in Kheis," *Turkish Online J. Educ. Technol.*, vol. 16, no. 2, pp. 35–42, 2017.
- [72] M. A. Al-Hawari and S. Mouakket, "The influence of technology acceptance model (TAM) factors on students' e-satisfaction and e-retention within the context of UAE e-learning," *Educ., Bus. Soc., Contemp. Middle Eastern Issues*, vol. 3, no. 4, pp. 299–314, 2010.
- [73] Y. J. Kim, J. U. Chun, and J. Song, "Investigating the role of attitude in technology acceptance from an attitude strength perspective," *Int. J. Inf. Manage.*, vol. 29, no. 1, pp. 67–77, 2009.
- [74] I. Arpaci, "Understanding and predicting students' intention to use mobile cloud storage services," *Comput. Human Behav.*, vol. 58, pp. 150–157, May 2016.



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