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RESEARCH ARTICLE

STUDENTS E-LEARNING ACCEPTANCE IN DEVELOPING COUNTRIES: LIBERIA

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ABSTRACT

The rapid advances in technology and the changes these advances have brought to people's lives have led to increased study of technology acceptance. Studies have shown that a factor such as behavioral intention affects college students' e-based learning acceptance. Despite the substantial amount of knowledge on the acceptance of technology, there was a gap in knowledge regarding the veracity of TAM undeveloped countries. Using the quantitative explanatory methodology, this study examines the predictive relationship between perceived usefulness, perceived ease of use, self-efficacy, and digital literacy of college students, and their behavioral intention (BI) to accept e-based learning. To test the hypothesis, questionnaire data were collected from 85 university students studying in Liberia, with random selection. Responses from the survey were analyzed utilizing the Partial Least Squares Structural Equation modeling (PLS-SEM). The results of this study indicated that perceived usefulness, perceived ease of use, self-efficacy, and digital literacy significantly explain students' BI to accept e-based learning, accounting for 56.7% of the variation in behavioral intention.

INTRODUCTION

Due to rapid advances in technology, universities and other institutions of higher education have been investing heavily in electronic-based learning (e-based learning) technologies such as Canvas, Blackboard, and Moodle to support delivery of academic curricular content (Liaw and Huang, 2013). Students' acceptance of e-based learning is critical to the successful and cost-effective implementation of such technology for academic purposes. Similarly, students' perception, skills, and knowledge regarding the use of technology play a significant role in the successful implementation of e-based learning initiatives. Researchers (e.g., Elkaseh *et al.,* 2016) have identified these student attributes as the major factors affecting their decision to accept and use a technology on a continuous basis. Davis (1989) established a technology acceptance model (TAM) that has been used in several technology acceptance studies in identifying and describing determinants of new technology acceptance (Alves and Lopes, 2015; Venkatesh *et al.,* 2003). It is not clear, however, whether the model is as applicable to e-based learning in developing countries as it appears to be in developed countries. Srite and Karahanna (2006) questioned the validity and generalizability of TAM because of a putative cultural bias when applied in countries other than those of the developed world. The present study addresses this concern by examining the relationship of key factors perceived usefulness (PU), perceived ease of use (PEOU), self-efficacy (SE), and digital literacy (DL) of students and students' intention to accept e-based learning in developing countries, which in-turn would extend the generalizability of TAM.

Statement of the problem: The use of technology has changed the structure and mechanics of instruction and learning in academic settings. Research has demonstrated the importance of technology acceptance as a key indicator of acceptance (Davis, 1989; Taylor and Todd, 1995). Indeed, for educational institutions wishing to promote the opportunity for their students to obtain and provide academic contents electronically, students' acceptance of such a technology is critical. Despite the substantial amount of knowledge on the acceptance of technology and the benefits of acceptance, no substantive studies have been conducted to test the veracity of TAM in undeveloped countries using the aforementioned factors. The determination that these factors are related to the acceptance of e-based learning in undeveloped countries as in developed countries can lead to the generalizability of TAM in undeveloped countries.

Theoretical framework: The technology acceptance model (TAM) is an extension of the theory of reasoned action (TRA; Fishbein and Ajzen, 1975) and is one of the most widely-used models in technology acceptance research. TAM describes and explains why users behave the way they do in relation to the acceptance of new technology. TRA, upon which TAM is based, suggests that individuals' intentions influence their behavior and that, respectively, individuals' behavior is a function of their attitude concerning that behavior (Ajzen, 1991, 1985; Fishbein and Ajzen, 1975). TRA is about intention and the antecedents that lead to the likelihood of success of the intended behavior (Ajzen, 1991; Er *et al.,* 2009). Essentially, TRA describes how users decide to execute a particular behavior and the reasons that users consider prior to deciding on executing or not executing a particular behavior. TAM is a theoretical model that has shown usefulness in explaining and predicting acceptance behavior by users of technology (Chen and Tseng, 2012; Guritno and Siringoringo, 2013). TAM is premised on two cognitive beliefs: perceived usefulness (PU) and perceived ease of use (PEOU). TAM proposes that users' BI to adopt a technology is controlled by their beliefs of PU and PEOU. Furthermore, the model found a significant relationship between beliefs about the usefulness of a technological system and the BI to use such technology (Davis, 1989; Venkatesh *et al.,* 2000). The present study examines the veracity of TAM in undeveloped countries.

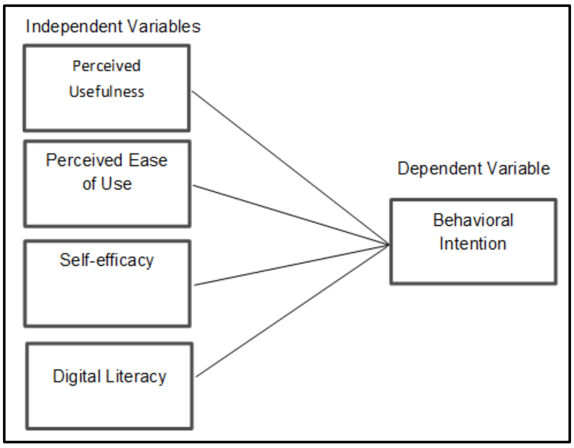

Figure 1. Conceptual model

Perceived Usefulness (PU): Perceived usefulness (PU) is a measure of the extent to which users believe that using a particular technological system has enhanced their performance (Chen and Tseng, 2012; Davis, 1989). The construct PU originated with TAM and, in this study, is defined as the degree to which students believe that using an e-based learning system will improve their academic performance. The strength of PU has been acknowledged in several studies to be an influential factor in determining users' intentions to accept a technology (Davis, 1989; Guritno and Siringoringo, 2013; Venkatesh *et al.,* 2003).

Perceived ease of Use (PEOU): Perceived ease of use (PEOU) concerns students' motivation and is the result of the students' assessment of an essential aspect of using a technology, such as its interfaces and the processes involved in its use (Davis, 1989). The PEOU construct originated with TAM, and studies have used it to measure users' acceptance of new technology (Elkaseh *et al.,* 2016; Liaw and Huang, 2013). Chang, Yan, and Tseng, (2012), for example, found that PEOU positively motivated the intention to use a technology. Relatedly, Elkaseh et al. (2016) found that PEOU had significant influence on the intention to use a technology.

Self-efficacy (SE): Self-efficacy (SE) is the degree to which users view themselves as capable of performing specific technology-related tasks (Ajzen and Fishbein, 1980). The SE construct originated Bandura (1977).Venkatesh *et al.* (2003) established that SE is an important determinant of BI in the acceptance of specific technologies, a result that has been confirmed by several researchers (e.g., Compeau and Higgins, 1995; Teo, 2009). Alenezi *et al.* (2010), for example, established that technological self-efficacy significantly influences the use of technology-related learning.

Digital Literacy: Digital literacy (DL) is the measure of a student's ability to use a digital technology (Buchnanan *et al.,* 2013; Markauskaite, 2007). Research has shown that students perceive digital literacy as being positively related to their acceptance of new technology (Buchnanan *et al.,* 2013; Mohammadyari and Sigh, 2015; Potosky, 2002).

Behavioral Intention (BI): For Ajzen (1991), behavioral intention (BI) deals with the likelihood that a user will engage in an intended behavior, which,for this study, is a student's willingness to pursue a task involving e-based learning.Several studies explored e-learning in developing countries (Chen and Tseng, 2012; Elkaseh *et al.,* 2016; Kituyi and Tusubira, 2013). Mohammad (2015) used a quantitative approach to explore the effects of PEOU, perceived usefulness on users' intentions towards use of e-based learning in Iran. He collected data through a survey and analyzed them via structural equations modeling (SEM). The results revealed that BI has positive effects on actual use of e-based learning. Perceived usefulness mediated the relationship between ease of use and users' intentions. Sánchez *et al.* (2013) investigated the factors that determine the acceptance of the Web CT learning system among students in Huelva. They collected d from a total of 226 students via a survey questionnaire that registered the subjects' responses to six constructs technical support, computer self efficacy, PEOU, PU, attitude, and system usage. The researchers employed SEM for modeling and data analysis. Results showed that Web CT usage and acceptance is directly influenced by PU and indirectly by PEOU. Tarhini, Hone, and Liu (2013) used quantitative methodology to validate an extended TAM an extension that included *social norms* and *quality of work life* constructs in Lebanon. They collected data from 569 undergraduate and postgraduate students actively studying in Lebanon via questionnaire and analyzed the data using SEM. They were able to determine that social norms and the quality of work life were significant determinants of students' BI and they were able to re-confirm the same results for PEOU and PU.

Hypotheses

This study tested the following hypotheses:

H1: PU significantly predicts the BI of college students' acceptance of e-based learning in developing countries.
H2: PEOU significantly predicts theBI of college students' acceptance of e-based learning in developing countries.
H3: SE significantly predicts the BI of college students' acceptance of e-based learning in developing countries.
H4: DL significantly predicts the BI of college students' acceptance of e-based learning in developing countries.

MATERIALS AND METHODS

The researcher sampled and surveyed college students studying full or part-time for graduate or undergraduate degrees in all disciplines. The researcher collected data through use of a questionnaire, which included 24 items. The questionnaire sampled PU using five items and PEOU using five items created by Davis (1989) and used with permission. The questionnaire also sampled SE using eight items and BI using three items created by Venkatesh *et al.* (2003) and used with permission. The remaining items were three to measure DL adopted from Kennedy et al. (2008). The questionnaire was closed-ended and subjects entered questionnaire responses with an ordinal 5-point Likert scale. The use of a quantitative methodology was essential since the study would deal with measurable relationships. Previous studies have used quantitative methodologies to understand non-quantitative relationships among the same variables (Orcher, 2005; Pollara and Broussard, 2011). To assist in maintaining a logical and focused flow in the questionnaire, the researcher grouped together questions that fell under particular constructs (e.g., questions about BI were grouped together). Of the 85respondents, 47 were male and 38 were female. The researcher combined metrics by summing the points associated with each of the constructs of the Likert scales. Table 1 presents the variables and questionnaire with item groupings.

Table 1. *Variables and Questionnaire*

Grouped Questions from the Questionnaire
Perceived Usefulness (PU), adopted from Davis (1989)
Q1: Using the system will allow me to accomplish learning tasks more quickly.
Q2: Using the system will improve my learning performance.
Q3: Using the system will make it easier to learn course content.
Q4: Using the system will increase my learning productivity.
Q5: Using the e-based learning system will enhance my effectiveness in learning.
Perceived Ease of Use (PEOU), adopted from Davis (1989)
Q6: Learning to operate the system is easy for me.
Q7: I find it easy to get the system to do what I want it to do.
Q8: My interaction with system is clear and understandable.
Q9: It is easy for me to become skillful at using the system.
Q10: I find the learning system easy to use.
Self-efficacy (SE), adopted from Venkatesh et al. (2003)
Q11: I could complete a job or task using the system if there was no one around to tell me what to do as I go.
Q12: I could complete a job or task using the system if I could call someone for help if I get stuck.
Q13: I could complete a job or task using the system if I had just the built-in help facility for assistance.
Q14: I could complete a job or task using the system if I had seen someone else using it before trying it myself.
Q15: I could complete a job or task using the system I would find the system easy to use.
Q16: I could complete a job or task using the system learning to operate the system is easy for me.
Q17: Thanks to my resourcefulness, I know how to handle unforeseen situations.
Q18: My interaction with the system would be clear and understandable.
Digital Literacy (DL), adopted from Kennedy et al. (2008)
Q19: Use the web to send or receive email.
Q20: Use the web to look up reference information for study purposes.
Q21: Use the web to create, edit and post assignment.
Behavior Intention, adopted from Venkatesh et al. (2003)
Q22: Given the chance, I intend to use the system to do different things, from downloading lecture notes and participating in chat rooms to learning on the Internet.
Q23: I predict I would use the system in the next semester.
Q24: In general, I plan to use the frequently for my coursework and other activities in the next semester.

This study statistical calculations involved use of the partial least square model (PLS-SEM). It also used the confirmatory factor analysis (CFA) to assess the constructs' reliability and validity; and it used the structural model approach to test the hypothesis (Hair *et al.,* 2013). According to Hair et al. (2013), the PLS-SEM approach can conceptually be used to answer research questions involving the direct or indirect observation of one or more independent or dependent variables, therefore justifying the use of PLS-SEM in this instance.

RESULTS

Descriptive analysis: The researcher calculated the means (M) and standard deviations (SD) on a five-point Likert scale to measure students' acceptance of e-based learning. As illustrated in Table 2, the subscales were PU, PEOU, SE, DL, and BI. The highest score was BI (M = 4.376, SD = .4732), and PU was the lowest (M = 3.857, SD = .5195).

Table 2. Descriptive Statistics

	N	Min.	Max.	Mean	Std. Deviation
PU	85	2.2	5	3.857	0.5195
SE	85	2.5	5	4.021	0.5341
PEOU	85	2.2	5	3.894	0.664
DL	85	2.333	5	3.989	0.7037
BI	85	2.666	5	4.376	0.4732
Valid N (listwise)	85				

Measurement model evaluation: The path models were established based on the 24 items that were grouped into five exogenous latent variables named PU, PEOU, SE, DL and BI. In PLS-SEM, the quality criterion for the model is required to achieve adequate levels of factorial, convergent, and discriminant validities along with internal consistency reliability.

Factorial and discriminant validity: The reader finds in Figure 2 the PLS path diagram drawn with the graphic user interface of Smart PLS. The indicators (i.e., the questionnaire item scores) are represented as rectangular symbols, and the latent variables (BI, SE, PU, PEOU, and DL) are represented as round symbols, which are operationalized by confirmatory factor analysis.

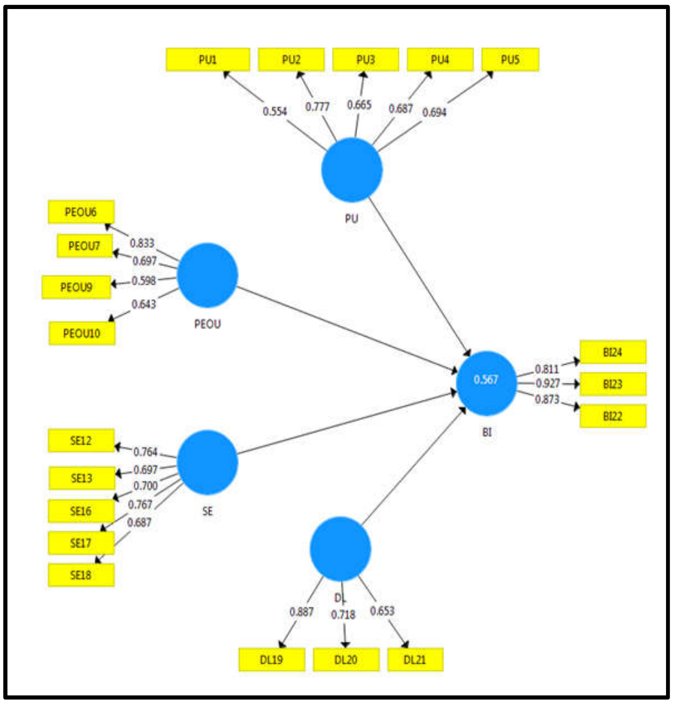

Figure 2. Measurement model

Factor loading coefficients (λ) are the numbers next to the arrows, which represent the directions and strengths of the correlations between the indicators and their associated latent variables using a standardized scale from -1 to +1. Table 3 presents the factor loading coefficients (λ) for all the indicators used to operationalize the three latent variables in the measurement model. Factorial validity was established because all the indicators used to operationalize the latent variables had strong ($\lambda \geq .5$) factor loading coefficients except for items PEOU8 ($\lambda = .294$), SE11($\lambda = .452$), SE14($\lambda = .478$), and SE15 ($\lambda = .466$), which were eliminated, based on Hair et al. (2013).

Discriminant Validity: The researcher used the Fornell-Larker criterion to assess the discriminant validity (DV), whereby the square roots of the average variance extracted for PU, PEOU, SE, and DL are compared to their relationships with the other predictor variables. Chin (1998) noted that DV is established when variables with average variance extracted (AVE) loading above 0.5. The bold values as represented in Table 3 show that the square-root of AVE whilst the other values represent the relationships between the respective variables. Hence, Table 4 shows that DV was established, since the bold values are higher than the relationships with the other latent variables.

Table 3. Factor Loading Coefficients

Factor Loading Coefficients					
	BI	DL	PEOU	PU	SE
BI22	0.87				
BI23	0.93				
BI24	0.81				
DL19		0.89			
DL20		0.72			
DL21		0.65			
PEOU10			0.64		
PEOU6			0.83		
PEOU7			0.7		
PEOU9			0.6		
PU1				0.55	
PU2				0.78	
PU3				0.67	
PU4				0.69	
PU5				0.69	
SE12					0.76
SE13					0.7
SE16					0.7
SE17					0.77
SE18					0.69

Table 4. Fornell-Larcker Criterion

Fornell-Larcker Criterion Measurements					
	BI	DL	PEOU	PU	SE
BI	**0.871**				
DL	0.646	**0.758**			
PEOU	0.322	0.592	**0.754**		
PU	0.577	0.51	0.443	**0.748**	
SE	0.585	0.564	0.59	0.592	**0.723**

Convergent Validity and Internal consistency Reliability: Table 5 shows that convergent validity and internal consistency reliability were established (after excluding the weak indicators PEOU8, SE11, SE14, and SE15).

Table 5. Quality Criteria for Measurement Model

Quality Criteria for Measurement Model			
	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
BI	0.84	0.904	0.759
DL	0.673	0.8	0.576
PEOU	0.661	0.789	0.57
PU	0.737	0.809	0.561
SE	0.785	0.846	0.524

The convergent validity is established when the AVE by their indicators for each latent variable is greater than 0.5 or 50%. As illustrated in Table 4, the convergent validity was established for PU, PEOU, SE, DL, and BI (AVE = 52.4% to 75.9%). As reflected in Table 5, high values of the composite reliability coefficients (0.789 to 0.904) and Cronbach's alpha (0.661 to 0.840) show that internal consistency reliability was good for each of the variables.

Evaluation of the structural model: To assess the effect of inhibiting factors, path diagrams were developed using PLS-SEM. The model assumes that PU, PEOU, SE, and DL are independent variables as reflected by the four-research hypothesis. The coefficient of determinant (R^2) as illustrated in Table 5 is the main criterion for goodness of fit. It signifies the degree of variance in the exogenous variables explained by the endogenous variables. As recommended by Ferguson (2009), the values of 4%, 25%, and 64% represent small, moderate, and strong effect respectively. The results of R^2 show that each latent variable has strong effect on BI. Stone-GeisserQ^2 (predictive relevance) serves as a preferred criterion to evaluate the inner model. As recommended, Q^2values greater than zero show a predictive relevance for the specific construct. The values of Q^2 in Table 5 are well above zero for the predictors, which show good predictive relevance for BI. In this study, the resultant effect size (f^2) is used to assess the strength of the correlations between the latent variables, which assist in assessing the overall contribution of the study. Cohen (1988) recommended values of 2%, 15% and 35% represent small, medium and large effects for a particular exogenous variable. The current model shows that DL has a large effect for BI, while SE, PU and PEOU have small effect on BI (see Table 6).

Table 6. Results of f^2, Q^2 and R^2

Results			
Predictors	f^2	Q^2	R^2
PU	0.093 > 0.02	0.208 > 0	25.80%
PEOU	0.095 > 0.02	0.180 > 0	27.50%
SE	0.110 > 0.02	0.202 > 0	31.10%
DL	0.318 > 0.35	0.473 > 0	50.10%

The researcher randomly sampled the data 5,000 times, with 85 cases in each sub-sample. The mean values of the β coefficients were computed, and two-tailed t tests were conducted to determine if the mean values were significantly different from zero at $p \leq .05$ (indicated by t>1.96). As illustrated in Table 6, all the T-statistics are larger than 1.96; thus, the researcher concludes that the outer model loadings are highly significant. Table 7 presents the computed t-values. The path coefficient between PU → BI (β = .258, t = 3.274, p<0.001), PEOU → BI (β = .273, t = 2.781, p<0.000), SE → BI (β = .311, t = 2.873, p<0.001), and DL→ BI (β = .501, t = 6.001, p<0.000) were significant (p<0.05).

Table 7. Results of Hypothesis Testing

Hypothesis Test Results					
H	Variables	β	T statistics	P Values	Results/Remarks
H1	PU → BI	0.258	3.274	0.001	Supported
H2	PEOU → BI	0.273	2.781	0.000	Supported
H3	SE → BI	0.311	2.873	0.001	Supported
H4	DL → BI	0.501	6.001	0.000	Supported

IMPLICATIONS OF THE STUDY'S RESULTS

A review of literature on the acceptance of technology indicated that there was a gap in knowledge regarding the veracity of TAM in undeveloped countries. This study cast PU, PEOU, SE and DL as independent factors to predict BI (dependent factor). The results of this study indicated that PU (R^2 = 25.8%), PEOU (R^2 = 27.5%), SE (R^2 = 31.1%), and DL (R^2 = 50.1%) significantly explain students' BI to accept e-based learning, accounting for 56.7% of the variation in BI. The findings suggest that students can more readily accept an e-based learning system once they have high DL, SE, PEOU, and PU. This study's findings reveal both theoretical and practice implications. Theoretically, this study sheds light on the interdependency of the mentioned constructs in technology acceptance in the context of e-learning, which is pivotal and helps increase understanding of e-learning acceptance and further confirms that explanatory power of TAM. This study provides insights into the intention of students regarding e-learning. Practically, the results presented in this study assist and help motivate institutions of higher education in Liberia to apply successful e-based learning applications.

Limitations of the research and future direction

Although the researcher took all necessary measures to eliminate any threat to the findings of this study, limitations remained. First, this study was cross-sectional in design, which meant the researcher could not manipulate the variables, and the collection of data was done at one time. Future research should extend the study by utilizing a longitudinal approach, which follows study's subjects over an extended period with repeated data collection throughout. Second, this study collected data through use of an online questionnaire. Third, to measure the constructs, the questionnaire included 24 items. Future studies should consider modifying the items.

DISCUSSION AND CONCLUSION

The path model assumed direct relationships between PU→ BI, PEOU→ BI, SE→ BI, and DL→ BI, casting them in the model as independent variables. The model established the relations between the latent variables and their relative dependent variable (BI), and accounted for a significant (R^2 = 56.7%) amount of the variation in BI. This research hypothesized that PU would significantly predict students BI to accept e-based learning in developing countries. The finding supported the hypothesis and showed that PU is an important factor in student BI to accept e-based learning, a finding supported by the Davis (1989), Guritno and Siringoringo (2013), and Venkatesh et al. (2003) studies. The present finding is important because it suggests that students engage in technology-based learning if they find it to be enjoyable and useful. This study hypothesized that PEOU would significantly predict students BI to accept e-based learning in developing countries. The findings supported this hypothesis. Students shape their behavior positively or negatively when they think a technology is beneficial and is relatively easy to use. Students prefer to avoid unnecessary details and complexities. Therefore, university administrators should be able to provide their students e-based learning systems which are easy to understand and operate and would, therefore, win sure acceptance. This study hypothesized that SE would significantly predict students BI to accept e-based learning in developing countries. The findings supported this hypothesis, which implies that students would use an e-based learning system if its use resulted in high levels of self-efficacy. This finding is supported by previous studies of Alenezi et al. (2010), Compeau and Higgins (1995), Teo (2009). Self-efficacy by itself is not a measure of a student's skills, but represents what students believe they can do based on their abilities or skills. Management support, involvement, and supervision from others positively influence students' self-efficacy to engage in e-based learning activities. If students with low technology self-efficacy can always call someone to help them while they face challenges in using e-based learning, they would not be forced to advance through the learning process by themselves, which may positively influence their self-efficacy levels. Therefore, educators should be aware that students' self-efficacy is a key controlling mechanism that affects their behavior and their judgments of their abilities to perform e-based learning-related tasks. This study hypothesized that DL significantly would predicts the BI of college students' acceptance of e-based learning in developing countries. The findings supported this hypothesis, implying that students with high digital literacy will be more likely to accept e-based learning. Weak digital literacy (DL) skills among students hampered the effective use of e-based learning systems. To overcome the lack of students' digital literacy, educational institutions should offer digital literacy training to their students. Digital literacy helps students develop a basic understanding of technology, such as e-based learning. The benefits of digital-technology can only be realized if students are empowered with the knowledge and skill to access and use them.Hence, for higher learning institutions in developing countries to implement and improve their e-based learning initiatives, they should formulate strategies for addressing critical factors, such as perceived usefulness, perceived ease of use, self-efficacy, and digital literacy, which are essential in enhancing students' behavioral intentions toward the acceptance of the technology. The results presented in this study are intended to assist and help motivate institutions of higher education in Liberia to apply successful e-based learning applications.

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