Assessing the Impact of E-learning Adoption on Learning Behavior in Sierra Leonean Higher Education

ABSTRACT

Aims: This study aims to analyze the adoption of e-learning in higher education institutions in Sierra Leone and its impact on learning Behavior using the Technology Acceptance Model (TAM).
Study design: The research employs a survey design, utilizing Structural Equation Modeling (SEM), to analyze the responses of students and lecturers.
Place and duration of study: The study was conducted in Sierra Leone, involving ten universities. The duration of the study is not specified.
Methodology: A total of 728 students and 327 lecturers were surveyed to assess their attitudes towards e-learning. The TAM was used to predict behaviors based on the perceived usefulness and ease of use of e-learning tools, such as mobile devices and social networking applications.
Results: The findings indicate that e-learning is more likely to be adopted if the tools are perceived as useful and easy to use. Additionally, prior experience with computers enhances the positive perception of e-learning's attributes and attitudes toward its utilization.
Conclusion: The study highlights the potential of e-learning in developing countries like Sierra Leone. It provides insights for stakeholders in the education sector to develop strategies that can promote the adoption of e-learning in regions with similar developmental profiles.

Keywords: E-learning adoption; Learning behavior; Computer experience; Behavioral intention; Perceived usefulness

1. INTRODUCTION

The advent of ICT has significantly transformed various sectors, including education. The integration of e-learning in higher education has become a global phenomenon, enabling institutions to extend their reach and enhance student access to quality education [1]. The growth of ICT has fostered the development of innovative distribution and learning methods, leading to meaningful learning experiences in academic settings [1,2]. However, the adoption of e-learning is not without challenges, particularly in countries where it is still in nascent stages. These challenges include a lack of ICT infrastructure, leadership, adequate training for instructors and learners, and a comprehensive e-learning strategy [1,2,3,4].

In developed countries like the USA, the UK, most European countries, and Australia, e-learning adoption in higher education is widespread and well-accepted [5,1]. Developing countries are also adopting e-learning to enhance educational experiences [6,7,8,9], but in Sierra Leone, this adoption faces unique challenges and is still in its early stages.

Critical Success Factors for e-learning adoption vary across countries due to differences in culture, policy, government regulation, and economic environments. Consequently, students' and teachers' perceptions of e-learning differ based on their cultural and educational backgrounds [10]. In Sierra Leone, traditional attitudes, customs, behaviors, and communication patterns still predominantly influence education, and there is a general lack of awareness about the potential of e-learning.

Despite some basic ICT infrastructure in public universities, Sierra Leone's higher education heavily relies on traditional face-to-face teaching methods, with most learning activities confined to campuses [11]. The COVID-19 outbreak has accelerated some government initiatives towards e-learning adoption, but significant challenges remain. These include a shortage of skilled teachers knowledgeable in ICT, financial constraints, lack of awareness and positive attitudes towards e-learning, insufficient technological infrastructure, and a lack of curriculum development for e-learning.

Given these challenges, this study aims to define and explore the factors critical for successfully implementing e-learning technology in Sierra Leone's higher education. The focus is on understanding academic staff's and students' perspectives on the factors influencing the adoption and implementation of e-learning for enhanced learning behavior in higher education. This research is novel in Sierra Leone, where e-learning is a relatively new experience in higher learning institutions. Examining lecturers' and students' experiences, perceptions, and intentions towards e-learning is crucial.

The study will comprehensively review core e-learning adoption and implementation factors in Africa, focusing on Sierra Leone. It aims to present the results and offer practical solutions and recommendations to facilitate e-learning adoption and implementation in Sierra Leonean higher education.

2. Theoretical Framework and Literature Review

2.1 Brief Reviews of Theoretical Model

The research on e-learning effectiveness and adoption in educational institutions extensively leverages theoretical models to understand the factors influencing technology acceptance. Among these models, the Technology Acceptance Model (TAM) [12], along with the Theory of Reasoned Action (TRA) [13] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [14], are prominently used [15,16,17]. This section reviews these models, particularly emphasizing TAM and its application in e-learning contexts.

2.1.1 Technology Acceptance Model (TAM)

Originating from the Theory of Reasoned Action, the Technology Acceptance Model (TAM) explains how users' beliefs and attitudes affect their decision to adopt or reject information technology. Central to TAM are two key concepts: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) [15,16], as identified by Davis et al., in his 1989 research. PU refers to a user's belief that using a specific system will enhance job performance, while PEOU relates to the belief that the system will be easy to use [18]. Davis’s research indicated that PU substantially influences user attitudes toward a system, about 50% greater than PEOU's [19].

TAM has been successfully applied to various technologies, evidencing its capability to predict technology adoption in domains such as e-banking, e-commerce, e-learning, and e-tax filing [20,21,15,16,17]. Studies within the realm of e-learning have particularly highlighted the significant role of PU and PEOU in shaping an individual's intention to use e-learning systems. The original TAM framework [15,16] proposed in Davis's research is illustrated in Figure 1.

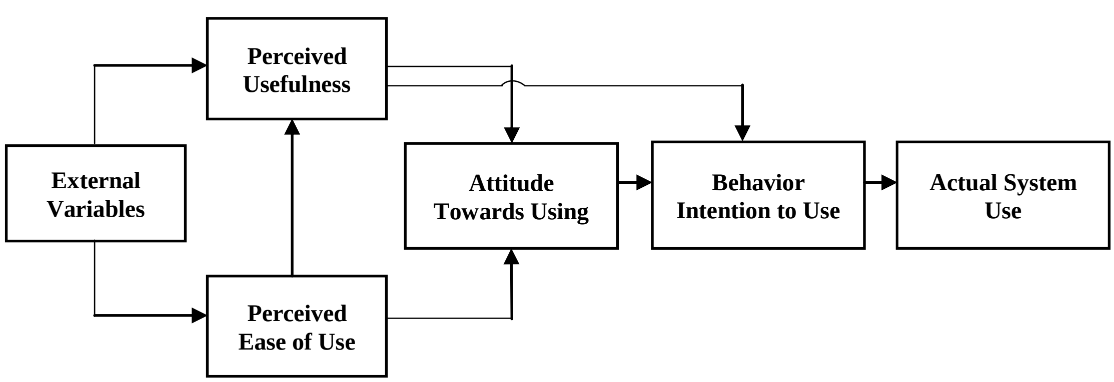


Figure 1 Original Technology Acceptance Model

2.2 Application of the Theoretical Model

Applying the theoretical model to the paper, TAM's utility in e-learning research is evident in its ability to predict user behavior across diverse e-learning platforms. Its focus on PU and PEOU provides valuable insights into designing and implementing user-centric e-learning systems [16,17].

2.2.1 Behavioral Intention to Use E-learning Technology

Ajzen's theory, as delineated by [13], posits that behavioral intention is a key indicator of an individual's readiness to engage in a particular action. Expanding on this concept, [22]clarified behavioral intention as the intensity of an individual's resolved intent to execute a specific behavior.

This construct is crucial for understanding the adoption and acceptance of new systems in various contexts, including e-learning [14,22,23, 24]. For this study, behavioral intention in the context of e-learning in Sierra Leonean higher education institutions is conceptualized as the willingness of individuals to embrace and utilize e-learning as a tool in teaching and learning.

2.2.2 Attitude Towards E-learning Behavior

'Attitude Towards E-learning Behavior' relates to an individual's positive or negative attitudes about participating in a specific behavior [25]. Bathaei and Hosseini (2014) described 'Attitude Towards Behavior' as the positive or negative evaluation one holds about performing a particular action [26]. There is a noted correlation between educators' attitudes toward technology and their success in using it for educational purposes [27]. Studies suggest a more positive attitude towards new technology is linked to a higher intention to use it [28]. In this research, 'Attitude Towards Behavior' in the Sierra Leonean higher education context is defined as the users' perception regarding the acceptance and utilization of e-learning.

2.2.3 Perceived Usefulness of E-learning

Perceived Usefulness (PU), as defined by [15,16], is the extent to which someone considers using a specific system would boost their job performance [15,16]. Venkatesh et al., (2003) expanded this definition, viewing PU as the level of improvement individuals anticipate by using a particular system [18]. The direct relationship between PU and Attitude Towards Use has been established in the context of e-learning acceptance and its impact on teachers' and students' technology usage [29]. Thus, in this study, PU of e-learning is defined as the extent to which students and teachers believe that e-learning will improve their teaching and learning effectiveness.

2.2.4 Perceived Ease of Use of E-learning

Perceived Ease of Use (PEOU) is the measure by which an individual considers using a particular system to be free of effort [15,16]. It encompasses system clarity, the ease of getting the system to perform desired tasks, the mental effort required, and overall user-friendliness [30]. PEOU, alongside PU, significantly influences the Behavioral Intentions to use a system [31]and is positively linked to PU [28]. Gong et al. (2004) described PEOU as the extent to which a prospective user assumes the target system to be effortless [32]. In this research, PEOU with e-learning is defined as the extent to which students and lecturers believe that using e-learning would be effortless.

2.3 Brief Review of the Literature

The literature on adopting and implementing e-learning systems has been extensive, with researchers focusing on various factors that influence its success. This review synthesizes some key studies to provide an overview of the field.

2.3.1 Related Literature on E-learning System Usage

The success of any ICT system, including e-learning platforms, heavily relies on user engagement. User acceptance, particularly among students and educators, is vital for the effective operation of e-learning systems. Research in different global contexts has shed light on various factors influencing this acceptance. In Malaysia, Al-rahmi et al. (2015) integrated the Technology Acceptance Model (TAM) with the Innovation Diffusion Theory (IDT) to explore the key factors affecting e-learning system usage among students [33]. (They identified several critical factors, including observability, relative advantages, trialability, complexity, perceived compatibility, and perceived enjoyment [33]. In the United Arab Emirates, a study by [34] found that trust, quality, innovativeness, and knowledge sharing significantly contribute to better acceptance of e-learning systems [34].

In Saudi Arabia, Al-Gahtani (2016) utilized the TAM model to identify the determinants of student acceptance of e-learning, highlighting factors such as anxiety, playfulness, and self-efficacy [35]. Another study in Saudi Arabia also proposed a new framework using the Delphi method, highlighting factors like technology options, website quality, and top management support as crucial for e-learning implementation [36]. Bellaaj et al. (2015) at the University of Tabuk, Saudi Arabia, employed the UTAUT model and found that effort and performance expectancy were significant predictors of e-learning acceptance [37].

Drawing on the comprehensive literature review, this study proposes a research model that integrates factors influencing online learners' engagement with a focus on the role of computer experience. This integration is visualized in Figure 2. The model is designed to capture the multifaceted nature of e-learning engagement and the nuanced impact of technological proficiency on learners' experiences and outcomes. Several hypotheses are formulated to systematically explore the relationships proposed in the model. These hypotheses are grounded in the theoretical foundations discussed in the literature review and are aimed at examining the dynamics between the key variables of online learner engagement and computer experience. The detailed hypotheses derived from the model will facilitate a structured investigation into how these factors interact and influence e-learning effectiveness in the context of higher education.

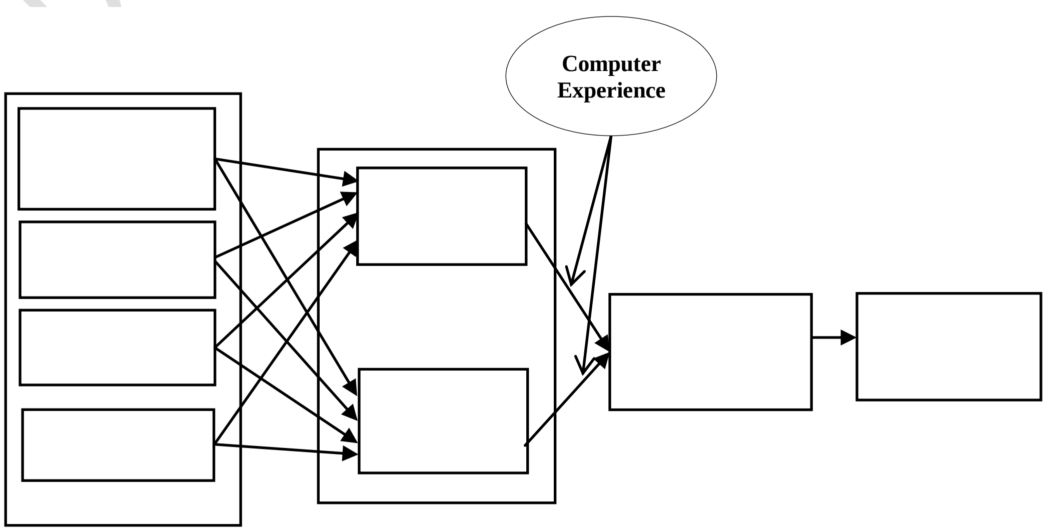


Figure 2 Research model

H1a: Social Networking Application use influences students' Perceived Usefulness of e-learning in Sierra Leonean higher education.

H1b: Social Networking Application Use Influences Lecturers' Perceived Usefulness of e-learning in Sierra Leonean higher education.

H2a: Social Networking Application use influences students' Perceived Ease of Use of e-learning in Sierra Leonean higher education.

H2b: Social Networking Application use influences lecturers' Perceived Ease of Use of e-learning in Sierra Leonean higher education

H3a: Perceived Entertainment positively impacts students' Perceived Usefulness of e-learning in Sierra Leonean higher education.

H3b: Perceived Entertainment positively impacts lecturers' Perceived Usefulness of e-learning in Sierra Leonean higher education.

H4a: Perceived Entertainment positively impacts students' Perceived Ease of Use of e-learning in Sierra Leonean higher education.

H4b: Perceived Entertainment positively impacts lecturers' Perceived Ease of Use of e-learning in Sierra Leonean higher education.

H5a: Social Influence positively impacts students' Perceived Usefulness of e-learning in Sierra Leonean higher education.

H5b: Social influence positively impacts lecturers' Perceived Usefulness of e-learning in Sierra Leonean higher education.

H6a: Social Influence positively impacts students' Perceived Ease of Use of e-learning in Sierra Leonean higher education.

H6b: Social Influence has a positive impact on lecturers' Perceived Ease of Use of e-learning in Sierra Leonean higher education.

H7a: Mobile Device usage influences students' Perceived Usefulness of e-learning in Sierra Leonean higher education.

H7b: Mobile Devices usage influences lecturers' Perceived Usefulness of e-learning in Sierra Leonean higher education.

H8a: Mobile Devices usage influences students' Perceived Ease of Use of e-learning in Sierra Leonean higher education.

H8b: Mobile Devices usage influences lecturers' Perceived Ease of Use of e-learning in Sierra Leonean higher education.

H9a: Perceived Ease of Use Influences Students' Attitude towards Behavior of Using e-learning in Sierra Leonean higher education.

H9b: Perceived Ease of Use influences lecturers' Attitude towards Behavior of using e-learning in Sierra Leonean higher education.

H10a: Perceived Usefulness influences students' attitudes towards e-learning in Sierra Leonean higher education.

H10b: Perceived Usefulness influences lecturers' Attitude towards Behavior of using e-learning in Sierra Leonean higher education.

H11a: Attitude Towards Behavior Influences Students' Behavioural Intention to Use e-learning in Sierra Leonean Higher Education.

H11b: Attitude Towards Behavior Influences Lecturers' Behavioural Intention to Use e-learning in Sierra Leonean Higher Education

H12a: Computer experience moderates the relationship between perceived usefulness and Attitude towards Behavior of e-learning in Sierra Leonean higher education.

H12b: Computer experience moderates the relationship between perceived ease of use and Attitude towards behavior e-learning in Sierra Leonean higher education.

3. Materials and Methods

To enhance the clarity and detail of the research methodology, the following improved text provides a more comprehensive overview:

Data for this study was meticulously gathered from ten Sierra Leonean higher educational institutions over one month, from November 10 to December 10, 2023, utilizing a systematically designed online survey. Prior to the deployment of the survey, a preliminary phase of engagement was conducted. This involved direct consultations with the heads of departments from the participating educational institutions. These discussions served a dual purpose: firstly, to delve into the challenges related to e-learning faced by these institutions and to elucidate the research objectives; secondly, to refine the focus on specific determinants influencing e-learning adoption, thereby enhancing learning behavior in these academic environments.

The questionnaire, structured to address distinct variables pertinent to the study, was meticulously crafted following these initial discussions. After these preliminary interactions, the department heads were requested to facilitate the survey dissemination. They established dedicated WhatsApp groups through which the survey link was shared. Emphasis was placed on maintaining the privacy and voluntary nature of participation. This is a point reiterated by the department heads and within the introductory section of the questionnaire itself. A target of 1,500 questionnaires was set, with 1,000 designated for students and 500 for lecturers across the universities. Of these, 728 student responses and 327 lecturer responses were deemed suitable for analysis after accounting for incomplete submissions, resulting in 71.5% and 64.6% response rates, respectively.

After data collection, the responses underwent rigorous processing, including cleaning, coding, and input into SPSS and AMOS software for detailed analysis. SPSS was utilized for conducting Factor Analysis and assessing Internal Consistency Reliability, while AMOS Version 21 facilitated the execution of Structural Equation Modeling (SEM). This modeling was pivotal in evaluating the hypothesized model's fit, scrutinizing the significance of proposed paths, and determining the explained variance (R^2) for each dependent variable.

The study's robustness was further underscored by the evaluation of six crucial goodness-of-fit indices: Chi-Square (χ^2) test, Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). Optimal model fit criteria were adhered to [38], with TLI, GFI, and CFI expected to exceed 0.90, χ^2/df ratio less than 3 [3940], AGFI above 0.80, and RMSEA below 0.08 [41].

Singh's analytic strategy (1995) explored the moderating effects within the structural model, leveraging a subgroup analysis approach [42]. This included both "unconstrained" and "fully constrained" multi-group assessments, with path coefficients permitted to vary in the former and held constant in the latter. The comparison of goodness-of-fit statistics for these models [38], based on the chi-square difference test, was instrumental in hypothesis testing.

4. Data Analysis and Results

This section presents a comprehensive demographic analysis of the study's participants drawn from a broad cross-section of ten higher educational institutions in Sierra Leone. The research targeted two key groups within these institutions: students and lecturers. A total of 1,500 questionnaires were distributed – 1,000 to students and 500 to lecturers. The response rate was impressive, with 715 students (yielding a 71.5% response rate) and 323 lecturers (resulting in a 64.6% response rate) providing completed questionnaires. This substantial response rate ensures a robust and representative sample for the study's analysis.

Demographic details have been meticulously collated and are presented in Table 1. This table categorizes participant information along several dimensions. For student participants, the data includes age and gender, offering insights into the diversity of the student body. For lecturers, the data is more expansive, encompassing age, gender, and the number of years dedicated to teaching. This additional metric for lecturers provides a deeper understanding of their experience and potentially their perspective on e-learning.

Furthermore, the survey explored participants' prior experience with e-learning platforms. This data collection aspect is particularly salient as it sheds light on the participants' level of familiarity and comfort with digital learning environments. Such insights are invaluable in assessing students' and lecturers' readiness and potential receptiveness to e-learning methodologies.

The amalgamation of these demographic variables offers a rich and nuanced understanding of the e-learning environment within Sierra Leonean higher education. By capturing diverse perspectives, this demographic analysis lays the foundation for a more informed and contextual interpretation of the study's findings regarding e-learning adoption and efficacy.

Table 1 Demographics characteristics and e-learning use

		Student		**Lecturers**	
		Frequency	(%)	Frequency	(%)
Gender	Male	407	56.92%	253	78.32%
	Female	308	43.08%	70	21.68%
Age	18-29	516	72.16%	27	8.36%
	30-49	199	27.84%	208	64.39%
	50+	0	0.00%	88	27.24%
Years of lecturing	0-5	NA	NA	63	19.50%
	6-10	NA	NA	175	54.18%
	10+	NA	NA	85	26.32%
Use E-learning as a Learning/Teaching Tool	Yes	715	100%	323	100%
	No	0	0.00%	0	0.00%
Using the Internet	Never	0	0.00%	0	0.00%
	Once a month	0	0.00%	0	0.00%
	Once a week	17	2.37%	0	0.00%
	Once a day	102	14.27%	105	32.51%
	More than once a day	596	83.36%	218	67.49%
Educational computer use	E-learning	461*	64.47%	187*	57.89%
	Computer-assisted instruction	513*	71.75%	219*	67.80%
	Others	286*	40.00%	77*	23.84%
Mobile devices used	Handphone	171*	23.92%	53*	22.84%
	Smartphone	708*	99.02%	319*	98.76%
	Laptop	698*	97.62%	317*	98.14%
	iPod	251*	35.10%	54*	16.72%
	Other	218*	30.49%	183*	56.66%
Activates usage with mobile devices	Making calls	703*	98.32%	317*	98.14%
	Sending/reading SMS	713*	99.72%	305*	94.43%

		Downloading	693*	96.92%	307*	95.04%
		Surfing the net	708*	99.02%	319*	98.76%
		Email	613*	85.73%	297*	90.81%
		Note-taking	644*	85.75%	174*	53.87%
Use Social networking media		Yes	714	99.86%	323	100%
		No	0[a]	0.00%	0	0.00%

*Respondents can answer more than one item. [NA] denotes not applicable, [a] denotes One respondent did not answer.

4.1 Results of Reliability and Validity of the Measurement Model

Table 2, presented below, provides a detailed analysis of unidimensionality and reliability for the study's constructs. The results affirm the unidimensionality of all items within their respective measurements, indicating a strong alignment of items within each construct. To assess internal consistency, Cronbach's Alpha (α) coefficients were computed, adhering to the standards set forth by [41]. According to these guidelines, Cronbach's Alpha should ideally be 0.7 or higher to confirm reliability.

Table 2 lists the Cronbach's Alpha values for each construct within the model. Notably, all constructs achieved Alpha values exceeding the 0.7 threshold, satisfying the internal consistency criteria. Additionally, the factor loadings for each construct surpassed the minimum acceptable value of 0.5 and attained statistical significance at $p < 0.001$, as suggested by [43].

Moreover, the study also tested convergent and discriminant validity across all constructs. Convergent validity was evaluated using Composite Reliability (CR) and Average Variance Extracted (AVE). As shown in Table 2, the results indicate that all CR values exceeded the 0.7 benchmark, while AVE values for all constructs were 0.5 or higher. This outcome signifies strong convergent validity for all constructs under study.

Therefore, after excluding any constructs that had loadings below the 0.5 mark, the analysis concludes that all the measures used in this study satisfactorily met the requirements for reliability and validity. This rigorous validation ensures the robustness and reliability of the constructs employed in the research model.

Table 2 Construct reliability

Constructs	**Items**	**Student Model**				**Lecturer Model**			
		Factor Loading	CR	Cronbach's Alpha (α)	AVE	Factor Loading	CR	Cronbach's Alpha (α)	AVE
Social Networking Application	SNA1	.873	.931	.894	.772	.873	.915	.822	.731
	SNA2	.896				.814			
	SNA3	.864				.861			
	SNA4	.882				.871			
Social Influence	SI1	.807	.897	.820	.746	.859	.886	.823	.722
	SI2	.821				.826			
	SI3	.956				.865			
Perceived Entertainment	PE1	.811	.907	.860	.766	.857	.876	.824	.703
	PE2	.943				.838			
	PE3	.868				.821			
Mobile Devices	MD1	.849	.885	.813	.721	.799	.846	.713	.648
	MD2	.836				.815			
	MD3	.863				.801			
Perceived Usefulness	PUS1	.858	.909	.835	0.769	.842	.872	.773	.696
	PUS2	.902				.870			
	PUS3	.871				.789			

Perceived Ease of Use	PEU1	.894	.927	.779	.762	.821	.902	.838	.698
	PEU2	.877				.793			
	PEU3	.852				.866			
	PEU4	.869				.861			
Attitude towards Behavior	ATB1	.926	.913	.859	.779	.840	.869	.864	.690
	ATB2	.840				.822			
	ATB3	.881				.830			
Behavioral Intention to Use	BIU1	.879	.924	.840	.802	.869	.886	.815	.723
	BIU2	.898				.785			
	BIU3	.911				.894			

Discriminant validity is achieved by comparing the square root of the AVE with their paired correlations shown in the diagonal of the correlation matrix in Table 3. Fornell and Larcker (1981) suggested that for discriminant validity to be satisfactory, the square root of the AVE from a construct should be higher than the correlation shared among the construct and other constructs in the model [42]. Table 3 shows that all the constructs were different from each other. The diagonal shows the square root of the AVE values of each construct, and these values were higher than the other correlation values between the constructs. Consequently, the results supported the discriminant validity of the measurement models.

Table 3 Factor correlation matrix with the square root of the AVE on the diagonal

	Matrix of Student Model							
	1	2	3	4	5	6	7	8
1 SNA	**.879**							
2 SI	.428	**.864**						
3 PE	.336	.337	**.876**					
4 MD	.230	.315	.314	**.849**				
5 PUS	.414	.529	.369	.419	**.877**			
6 PEU	.341	.332	.116	.137	.390	**.873**		
7 ATB	.372	.354	.306	.250	.399	.255	**.883**	
8 BIU	.270	.312	.316	.251	.355	.157	.511	**.896**
	Matrix of Lecturer Model							
1 SNA	**.855**							
2 SI	.331	**.850**						
3 PE	.474	.360	**.839**					
4 MD	.377	.296	.497	**.805**				
5 PUS	.479	.423	.633	.532	**.834**			
6 PEU	.557	.380	.456	.106	.167	**.836**		
7 ATB	.310	.266	.402	.233	.377	.064	**.831**	
8 BIU	.276	.270	.449	.282	.440	.069	.550	**.851**

Note: Diagonals represent the square roots of AVE, and the other Matrix entries are the factors' correlations.

To investigate the goodness-of-fit of the proposed measurement models, six indices were used, namely the □ 2-square test, the goodness-of-fit index (GFI), the adjusted goodness-of-fit index (AGFI), the comparative fit index (CFI), the Tuker-lewis Index (TLI) and the root mean square error of approximation (RMSEA). Table 4 shows goodness-of-fit indices in the measurement models.

Table 4 Results of the models' goodness-of-fit

Model Fit Indices	**Criteria**	**Values**

		Student Model	Lecturer Model
χ^2/df	< 3.0	1.951	1.604
Goodness-of-fit index (GFI)	≥0.90	0.935	0.937
Tuker-Lewis Index (TLI)	≥0.90	0.928	0.941
Comparative Fit Index (CFI)	≥0.90	0.972	0.976
Adjusted Goodness-of-fit Index (AGFI)	≥0.90	0.926	0.943
Root Mean Square Error of Approximation (RMSEA)	<0.08	0.036	0.041

The evaluation of the model's goodness-of-fit yielded results that affirm an acceptable alignment with the empirical data. For both the student and lecturer models, the Chi-square (χ^2-square) values were notably below the recommended threshold of 3, registering at 1.951 and 1.604, respectively. This suggests a good fit between the hypothesized model and the observed data.

Additionally, the Goodness-of-Fit Index (GFI) surpassed the minimum acceptable level of 0.90 for both models, with the student model achieving a GFI of 0.935 and the lecturer model a GFI of 0.927. This indicates a high degree of fit between the observed data and the estimated model. Similarly, the Adjusted Goodness-of-Fit Index (AGFI) values, which account for the number of predictors in the model, were well above the 0.9 benchmark, standing at 0.926 for students and 0.943 for lecturers. These figures denote a reliable model fit considering the number of variables involved.

The Comparative Fit Index (CFI), which compares the fit of the target model to a null model, also demonstrated strong results. The student model's CFI was 0.972, and the lecturer model's CFI was 0.976, both comfortably exceeding the 0.9 standard and indicating a robust model fit. Furthermore, the Tucker-Lewis Index (TLI) values for both models exceeded the recommended level of 0.9, with scores of 0.928 and 0.941 for students and lecturers, respectively. This signifies that the models are well-fitting when considering the model's complexity.

Lastly, the Root Mean Square Error of Approximation (RMSEA) values, a measure of model discrepancy per degree of freedom, were well within the desired limit of 0.08, recording values of 0.036 and 0.041 for the student and lecturer models, respectively. This denotes a close fit of the model to the data.

These indices collectively suggest a strong goodness-of-fit for the models as per the commonly accepted thresholds in the extant literature [38,44]. Table 4 in the study provides a detailed presentation of these fit indices, further confirming the appropriateness and robustness of the models in representing the studied phenomena.

4.2 Analysis of Path Coefficients of the Structural Models

In the structural model tailored for students, several key factors were classified as significant contributors to the perception of e-learning. Notably, the integration of Social Networking Applications, Perceived Entertainment, Social Influence, and the use of Mobile Devices accounted for a substantial 57% of the variance in Perceived Usefulness. This indicates that these elements are pivotal in shaping students' beliefs about the effectiveness and benefits of e-learning platforms.

The same set of factors – Social Networking Applications, Perceived Entertainment, Social Influence, and Mobile Devices – also played a crucial role in influencing Perceived Ease of Use, explaining 48% of its variation. This finding suggests that these variables significantly impact the user-friendliness and accessibility of e-learning systems. Furthermore, the model reveals that Perceived Usefulness and Perceived Ease of Use collectively account for 55% of the variation in Attitude towards Behavior. This implies that students' overall sentiment and disposition toward e-learning are primarily shaped by how useful and easy to use they perceive the technology.

Regarding behavioral outcomes, the model demonstrates that these factors explain 52% of the variability in students' Intention to use e-learning. This underscores the substantial impact of the variables above on students' readiness to engage with e-learning systems.

The extent of the influence of each factor on the dependent variables within the students' model is quantitatively depicted in Figures 3a and 3b, where the multiple squares correlation R2 values are presented. These values offer a clear, numeric representation of how much each independent variable contributes to explaining the variance in the respective dependent variables, providing valuable insights into the dynamics driving e-learning adoption among students.

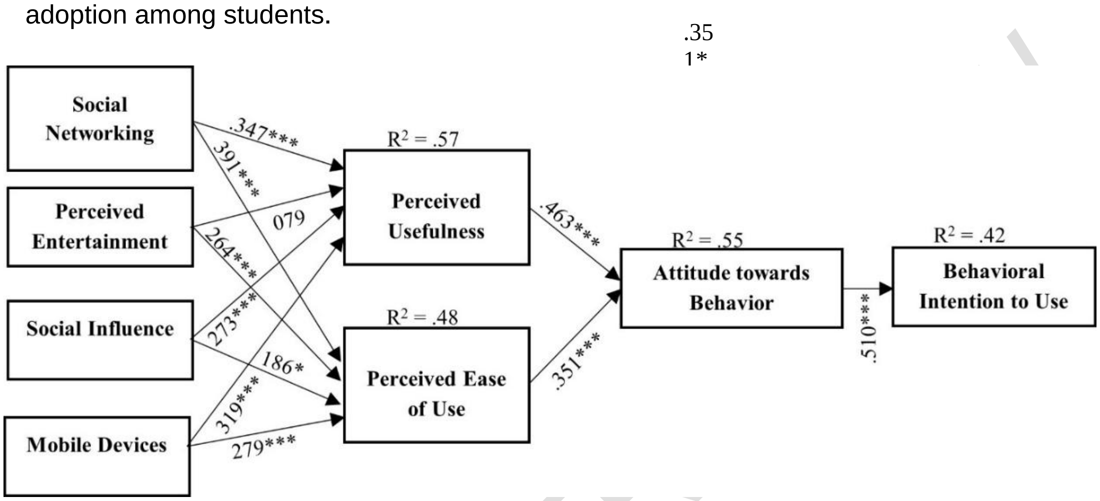


Figure 3a Results of structural model of students
*p < 0.05; **p < 0.01; ***p < 0.001

In the structural model specifically designed for lecturers, a significant portion of the variance in their perceived usefulness of e-learning was accounted for by key factors. Specifically, Social Networking Applications, Perceived Entertainment, Social Influence, and Mobile Devices collectively explained 62% of this variance. This high percentage highlights these factors' substantial impact on lecturers' perceptions regarding the utility of e-learning platforms.

Furthermore, the model revealed that these factors – Social Networking Applications, Perceived Entertainment, Social Influence, and Mobile Devices – were also instrumental in explaining 51% of the variance in Perceived Ease of Use of e-learning. This indicates that these elements significantly influence lecturers' perceptions of the effortlessness and accessibility of e-learning systems.

Additionally, an impressive 69% of the variance in lecturers' Attitude towards the Behavior was elucidated by Perceived Usefulness and Perceived Ease of Use. This underscores the strong influence that the perceived benefits and user-friendliness of e-learning platforms have on shaping lecturers' overall attitudes toward adopting these technologies.

In a comprehensive view, the model for lecturers successfully explained 63% of the variance in their Intention to Use e-learning. This considerable percentage reflects the model's effectiveness in capturing the key factors that drive lecturers' willingness to engage with e-learning platforms.

The detailed breakdown of the multiple square's correlation R2 for each dependent variable within the lecturers' model is systematically illustrated in Figure 4. This figure provides a clear visual representation of how each independent variable contributes to explaining the variance in the respective dependent variables, offering valuable insights into the factors influencing lecturers' adoption and utilization of e-learning in their teaching practices.

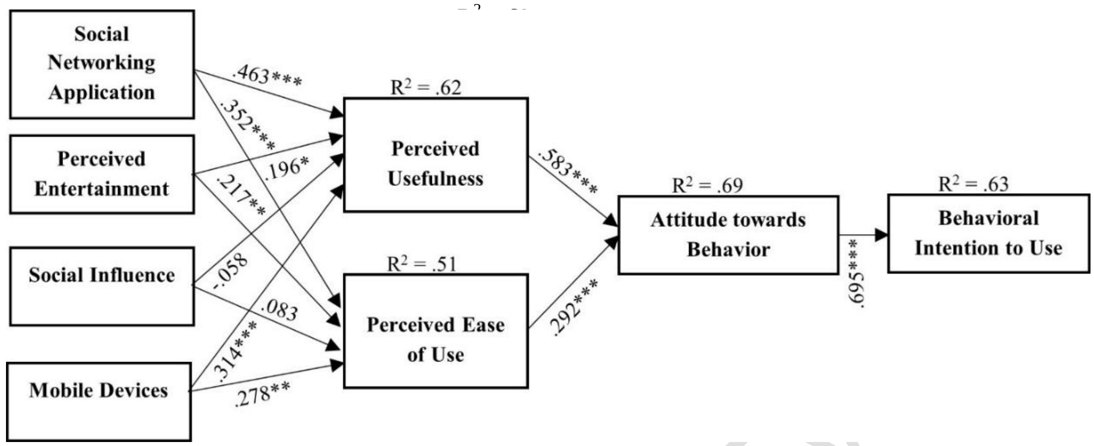


Figure 3b Results of structural model of lecturers
*p < 0.05; **p < 0.01; ***p < 0.001

4.3 Test of Hypothesis

The analysis of the Structural Equation Models, as depicted in Figures 3a and 3b, provides insightful findings regarding the hypothesized relationships within the models for both students and lecturers. Most of these relationships were confirmed to be statistically significant, underscoring the robustness of the proposed theoretical framework.

For the student model, the relationship between Perceived Usefulness and Social Networking Application emerged as statistically significant ($\beta = .347$, $p < 0.001$), corroborating the hypothesized connection. Similarly, statistically significant relationships were identified between Perceived Usefulness and both Social Influence and Mobile Devices and between Perceived Ease of Use and the factors of Social Networking Applications, Perceived Entertainment, Social Influence, and Mobile Devices. Furthermore, Attitude Towards Behavior and Perceived Usefulness and Attitude Towards Behavior and Perceived Ease of Use exhibited significant associations. Additionally, a significant influence of Attitude Towards Behavior on Behavioral Intention to Use e-learning was noted. However, the hypothesized link between Perceived Usefulness and Perceived Entertainment did not attain statistical significance ($\beta = .079$, $p > 0.05$), leading to the non-support of this path.

Regarding the specific hypotheses, H1a, H5a, and H7a were supported for the student model, indicating significant predictions of Perceived Usefulness by Social Networking Applications, Social Influence, and Mobile Devices. However, H3a was not supported. The hypotheses H2a, H4a, H6a, and H8a, related to Perceived Ease of Use, were all supported, validating their respective predictors. Hypotheses H9a and H10a, concerning Attitude toward Behavior, were also supported, as were the connections posited in hypothesis H11a.

In the lecturer model, the paths between Perceived Usefulness and Social Networking Applications, Perceived Usefulness and Perceived Entertainment, and Perceived Usefulness and Mobile Devices were all found to be statistically significant, supporting the related hypotheses H1b, H3b, and H7b. Contrarily, the paths linking Perceived Usefulness and Social Influence and Perceived Ease of Use and Social Influence did not achieve statistical significance, leading to the rejection of hypotheses H5b and H6b. The findings support the remaining hypotheses, H2b, H4b, and H8b, regarding Perceived Ease of Use and H9b and H10b related to Attitude towards Behavior. Hypothesis H11b, highlighting the effect of Attitude towards Behavior on Behavioral Intention to Use e-learning, was also confirmed.

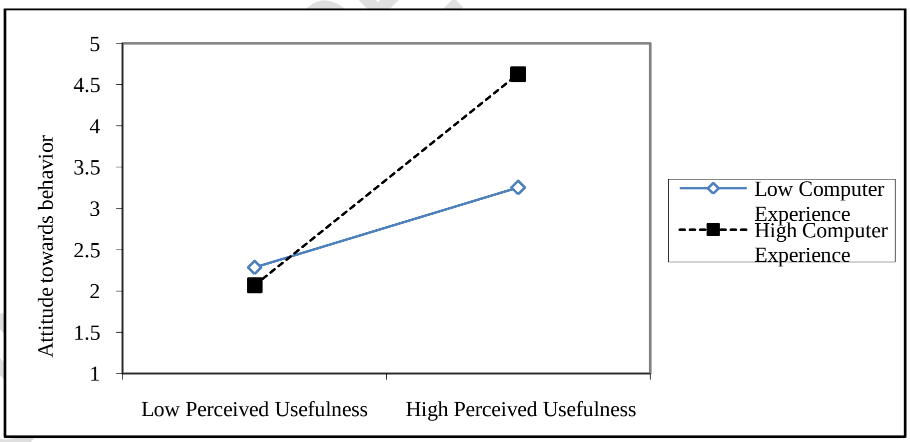
These results demonstrate a nuanced understanding of the factors influencing e-learning adoption among students and lecturers, revealing the intricate interplay of social influences, technological perceptions, and attitudinal factors in shaping their intentions to use e-learning platforms.

4.4 Moderating Effects of Students and Lecturers' Computer Experience

The examination of the moderating effects of computer experience on the proposed model is illustrated through a high-low analysis, as depicted in Figures 4 and 5. The study employed a slope interaction test to assess these moderating effects rigorously. This methodological approach is pivotal for understanding how varying levels of computer experience among participants influence the strength and direction of the relationships within the e-learning adoption model.

The slope interaction test explicitly enables a more granular analysis by comparing the slopes of regression lines for groups with high versus low levels of computer experience. By analyzing these differences, the study can ascertain whether computer experience significantly modifies the relationships between key constructs like Perceived Usefulness, Perceived Ease of Use, Attitude Towards Behavior, and Behavioral Intention to Use e-learning. This method enhances the robustness of the findings and provides valuable insights into how e-learning adoption dynamics differ across various levels of computer proficiency.

Incorporating this nuanced approach allows for a deeper understanding of the role of computer experience in e-learning adoption, offering more tailored and effective strategies for implementation in higher education institutions, particularly in Sierra Leone. Figures 5 visually represent these interactions, enabling a clear interpretation of how computer experience acts as a significant moderating factor in the e-learning adoption process.



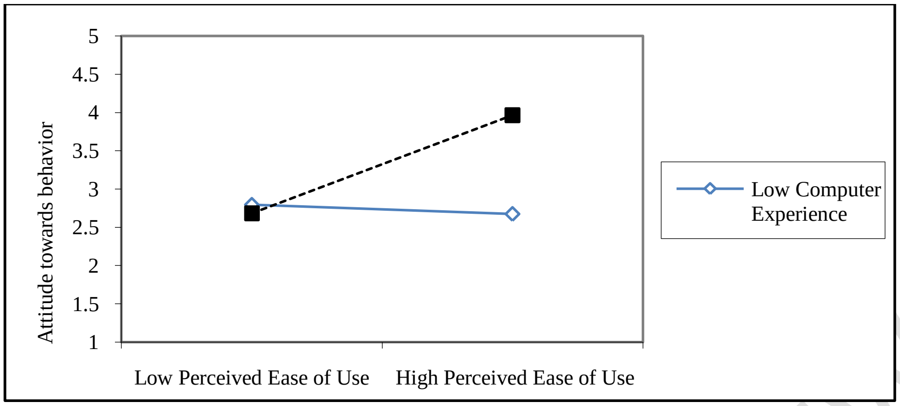
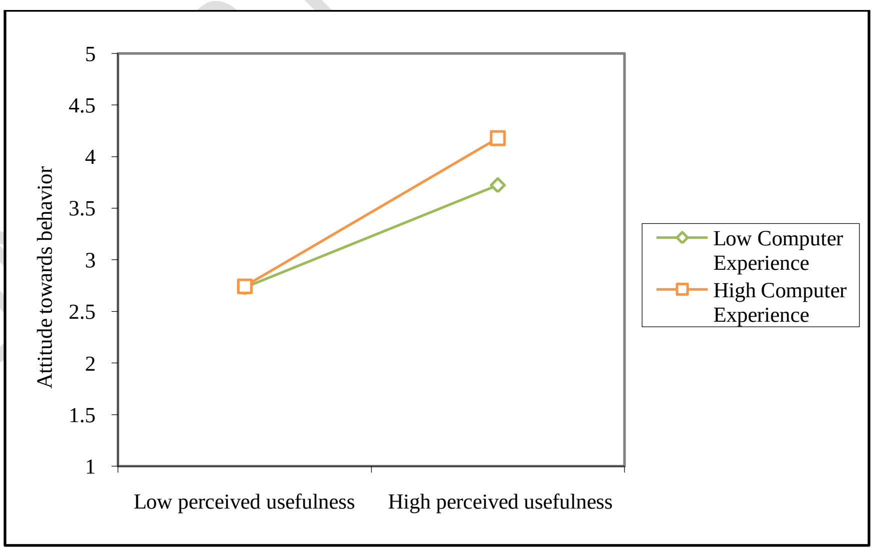


Figure 4 Moderating effects of students' computer experience

Figure 4 presents compelling evidence that Computer Experience (CE) significantly amplifies the positive relationship between Perceived Usefulness (PUS) and Perceived Ease of Use (PEU), as well as Attitude Towards Behavior (ATB) in the e-learning adoption process. This enhancement underscores the critical role of computer experience in fostering the effective adoption of e-learning platforms. The slope interactions demonstrate the pivotal influence of computer proficiency on the perceived utility of e-learning systems, indicating that higher levels of computer experience led to a more pronounced appreciation of these systems' usefulness and ease of use.

The moderation effect of computer experience is not just a statistical observation but a practical insight, suggesting that e-learning strategies in Sierra Leone's higher education can be significantly optimized by enhancing computer literacy and experience among users. This finding aligns with assertion that innovative antecedents are essential for successful e-learning adoption [45]. The presence and improvement of computer experience among students and educators are instrumental in accelerating the adoption and practical implementation of e-learning, thereby advancing the overall functionality and effectiveness of digital education platforms in Sierra Leone.



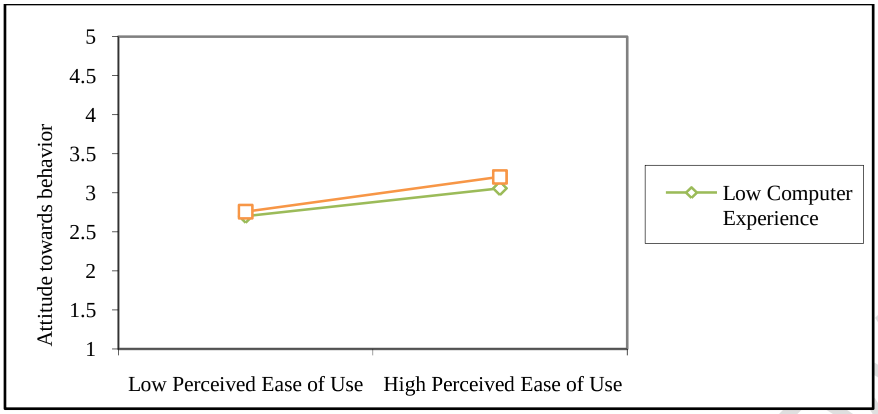


Figure 5 Moderating effects of lecturer computer experience

Figure 5 further elucidates the moderating role of CE, showing that the influence of PUS and PEU on ATB is more pronounced when computer experience is high. This implies that individuals with greater familiarity and comfort with computer technology are more likely to perceive e-learning systems as valuable and easy to use and, consequently, develop a more favorable attitude toward their adoption. This insight is particularly relevant for educational policymakers and administrators aiming to enhance e-learning adoption rates. By prioritizing computer skills training and development, higher education institutions in Sierra Leone can create a more conducive environment for effective e-learning adoption, ultimately leading to enhanced learning outcomes.

4.5 Discussion of the Results

This comprehensive study explores the adoption and implementation of e-learning in Sierra Leone's higher education. The research investigates factors influencing university lecturers' and students' acceptance and use of e-learning technologies. Anchored in the empirical literature on Information Technology adoption, the study extends four pivotal factors—related to attitudes and intentions—within the Technology Acceptance Model (TAM). Consequently, the research framework comprises eight distinct constructs, visually represented in Figure 2.

In both student and lecturer models, significant influences of social networking applications, social influence, and mobile devices are observed on the perceived ease of use and perceived usefulness of e-learning platforms. These factors, in turn, profoundly impact the Attitude towards Use, which crucially affects the intention to adopt e-learning. This pattern suggests that individuals are more inclined to utilize e-learning technologies in Sierra Leonean universities when they perceive social networking applications and mobile devices as beneficial tools.

Adamson's research [46]highlights the importance of Social Networking Applications (SNA) in the educational context, suggesting their extensive use for effective teaching and learning. Similarly, Jackson in 2011 emphasizes the positive influence of SNA usage on student learning outcomes in educational institutions [47]. This study probes into the role of SNA in e-learning, examining its correlation with the Perceived Usefulness and Perceived Ease of Use in the Sierra Leonean higher education context. The study underscores the critical nature of SNA in the adoption process of e-learning in Sierra Leonean higher education, demonstrating that SNA significantly influences both Perceived Ease of Use and Perceived Usefulness among students and lecturers. Consequently, the ease of use and perceived benefits of social media platforms significantly heighten the likelihood of e-learning technology adoption for educational purposes in Sierra Leone.

Moreover, the study reveals a robust relationship between the ease of use of SNA and the acceptance of e-learning, aligning with findings by [48], who observed a high likelihood of e-learning technology acceptance among students and teachers who extensively utilize SNA. This high SNA usage rate positively influences perceptions regarding the ease of use of e-learning technology among students and lecturers in Sierra Leonean higher education.

The study also discovers that Perceived Entertainment (PE) significantly influences students’ ease of use perceptions concerning e-learning, resonating with findings by [49,50]. However, contrary to these findings, the study notes that PE does not significantly impact students’ Perceived Usefulness of e-learning. For lecturers, PE notably affects both Perceived Usefulness and Perceived Ease of Use of e-learning, consistent with the observations [51,52]. PE's influence on Perceived Usefulness and Perceived Ease of Use suggests that enjoyable and engaging e-learning experiences can facilitate its adoption and use among lecturers.

Social Influence (SI), while significantly affecting students' Perceived Usefulness and Perceived Ease of Use of e-learning, does not play a similarly pivotal role in influencing lecturers’ Behavioral Intention to Use e-learning. This distinction implies that while peers and social groups impact students' intention to use e-learning, they do not similarly influence lecturers. This discrepancy aligns with findings from previous studies (e.g., [53,54].). This is consistent with Davis et al., (1989), who found that SI had a limited effect on intentions beyond perceived usefulness and perceived ease of use, particularly among male lecturers [55,56].

Mobile device (MD) usage by students and lecturers influences the Perceived Usefulness and Perceived Ease of Use of e-learning. This finding is supported by previous research indicating the importance of past experiences with specific technologies for future technology adoption [13,57,58,59]. This study corroborates with [60]in highlighting that frequent use of MDs facilitates the acceptance and use of e-learning. Conversely, infrequent MD users or those with limited technological proficiency are less inclined to perceive e-learning as easy or useful, as suggested [61].

In summary, this study offers valuable insights into the key factors influencing the adoption and implementation of e-learning in Sierra Leonean higher education. It emphasizes the critical role of social networking applications, mobile device usage, perceived entertainment, and social influence in shaping students' and lecturers' perceptions and attitudes toward e-learning, influencing their behavioral intention to adopt these technologies.

4.6 Implications

The study's findings are crucial for policymakers and educators in Sierra Leone's higher education sector, emphasizing the significance of understanding and addressing factors that influence the acceptance and use of e-learning among students and lecturers. These insights can guide decision-makers in recognizing and implementing key success factors for effective e-learning adoption, considering both theoretical aspects (like the role of technology in education) and practical aspects (like enhancing digital literacy and integrating user-friendly e-learning tools).

4.6.1 Theoretical Implications

The study enriches existing literature by exploring the influence of social networking applications, mobile devices, and perceived entertainment on adopting e-learning in Sierra Leonean higher education. It underscores the critical role of these external factors in shaping students' and lecturers' perceptions of e-learning's ease of use and usefulness.

4.6.2 Practical Implications

Higher education institutions should integrate social networking tools and mobile technologies to enhance e-learning platforms, making them more user-friendly and accessible.

Developing training programs to improve digital literacy among students and educators can enhance engagement and adoption of e-learning.

4.6.3 Recommendations

Implement policies that encourage the integration of advanced ICT in educational settings and invest in improving internet infrastructure to support e-learning. Focus on standardizing e-learning platforms across institutions to ensure uniform quality and accessibility. Develop context-specific e-learning content and invest in robust ICT infrastructure.

5. Conclusion

The study explored factors influencing the adoption of e-learning in Sierra Leonean higher education, focusing on students' and lecturers' perspectives. It developed a theoretical model integrating various constructs related to attitudes and intentions within the Technology Acceptance Model framework. The research findings indicate that factors like Social Networking Applications, Social Influence, Mobile Devices, and Perceived Entertainment significantly impact both Perceived Ease of Use and Perceived Usefulness of e-learning. The study's innovation lies in its comprehensive approach, providing a nuanced understanding of e-learning adoption in the context of Sierra Leone. It emphasizes the role of external factors (e.g., social networking applications and mobile devices) in influencing e-learning adoption. It highlights the moderating role of computer experience on the relationship between perceived e-learning features and attitude toward Behavior. This research contributes significantly to the literature by offering insights specific to Sierra Leone, which can inform policy and practical applications in similar contexts.

AVALAIBILITY OF DATA AND MATERIAL SECTION

The datasets generated and analyzed during the current study are not publicly available due to privacy and ethical considerations but are available from the corresponding author upon reasonable request.

ETHICAL APPROVAL

This complies with the participating institutions' data protection policies and our research's ethical guidelines. Specific data subsets or analytical methods used in the study can be provided upon verified academic request, ensuring all data sharing complies with applicable data protection laws and institutional policies.

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