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PAPER

Navigating Anxiety in a Cloud E-learning Virtual Environments: The Moderating Role of Anxiety on Lecturers' Adoption of Cloud Computing E-learning

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ABSTRACT

The rapid expansion of cloud computing e-learning systems has empowered educators to reach learners worldwide. However, a critical study gap exists: the impact of lecturers' technological anxiety on their adoption intentions remains unexplored in the technical universities in Ghana. This study addresses this gap by investigating anxiety's influence on lecturers' cloud computing e-learning adoption intentions within a virtual environment (VE). We examine the mediating role of competitive pressure and the moderating role of anxiety. Using PLS-SEM, we analysed data from surveys conducted among 1395 lecturers across all 10 technical universities. With a high response rate of 90.2% (n = 1258), our analysis reveals moderate anxiety among lecturers regarding cloud e-learning adoption. The proposed model explains 21.1% of the variance in adoption intentions. Interestingly, competitive pressure on lecturers mediates the relationship between cloud e-learning usefulness, security, and adoption decisions. Additionally, anxiety moderates the effects of cloud computing complexity, security, and adoption intentions. We have recommended organizing regular training workshops, ensuring user-friendly platforms, implementing robust security measures, and providing psychological support for lecturers using cloud computing technologies.

KEYWORDS

anxiety, virtual environment (VE), cloud computing, e-learning technologies, technical university, structure equation modelling (SEM), moderation, smartPLS

1 INTRODUCTION

The rapid advancement of technology has transformed education, with cloud computing emerging as a key tool for enhancing delivery and management in tertiary institutions. Cloud computing facilitates e-learning by providing scalable, flexible, and cost-effective solutions. Its integration into virtual learning environments

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has revolutionized the landscape, offering unprecedented opportunities for flexible, accessible, and collaborative learning [1]. Cloud e-learning virtual environments (VE) integrate online education with simulated environments and diverse educational tools to create more captivating and interactive learning experiences. As a result, educational institutions are increasingly integrating it into traditional classroom instruction to create innovative pedagogical strategies that combine formal and informal learning modalities [2]. This aims to improve learning effectiveness and overcome limitations inherent in traditional platforms.

However, this digital paradigm shift presents challenges for educators. The development and adoption of cloud e-learning virtual environments can be hindered by individual psychological factors, particularly technology anxiety [3]. Technology anxiety, characterized by discomfort, fear, and tension towards new technologies, can impact educators' decision-making and the effectiveness of technology use in education investigations [4], [5]. The rapid shift to online learning during COVID-19 highlighted this challenge, with many universities struggling due to educators' negative attitudes and resistance to using online tools [6–8]. This resistance can be linked to technology anxiety, potentially hindering the perceived usefulness and adoption of e-learning [9], [10].

Despite the documented benefits of cloud computing in education, a gap exists in understanding how anxiety affects the relationship between e-learning factors and their effectiveness in Ghanaian technical universities. This study aims to address this gap by focusing on lecturers at technical universities in Ghana, a population facing increasing pressure to adopt cloud computing-based e-learning. No prior study has specifically investigated e-learning adoption anxiety among this group, making our study a valuable contribution. Existing studies in traditional universities primarily focused on online education development and adoption [11–13], neglecting the psychological and behavioural aspects, particularly lecturer e-learning anxiety. This study uniquely involved all 10 technical universities in Ghana, providing a more comprehensive and representative analysis compared to studies relying on limited samples.

Our study aims to:

i) Investigate the prevalence of cloud computing e-learning adoption anxiety among lecturers in a virtual environment.
ii) Explore the mediating role of competitive pressure on lecturers in the relationship between cloud computing e-learning usefulness, cloud computing e-learning security, and lecturers' e-learning adoption within a virtual environment.
iii) Examine how cloud computing and e-learning anxiety moderate the relationship between the investigated factors.

This study offers significant contributions. By investigating the impact of lecturer anxiety and competitive pressure on e-learning adoption in Ghana, we provide insights that can inform educational policies in Ghana and other developing economies. Ultimately, our findings can guide the development of effective e-learning systems globally, with a specific focus on addressing psychological barriers to technology adoption. This enhanced understanding can inform improved policy decisions, foster global educational growth, and ultimately improve the quality of education.

The paper is organized as follows: Section 2 presents a comprehensive review of the relevant literature. Section 3 details the materials and methodology used for study design and data gathering. Section 4 outlines the analysis and results, while Section 5 provides a subsequent discussion of the results. Section 6 concludes the study with a discussion of its limitations and suggestions for future study.

2 LITERATURE REVIEW

Anxiety in e-learning has become a significant area of concern, especially with the transition to online learning methods. This shift to cloud computing e-learning has resulted in increased rates of anxiety, depression, and fatigue among educators and students, ultimately diminishing their motivation for e-learning [14]. Anxiety can negatively impact various aspects of the e-learning experience, including class preparation, academic performance, and even memory retention [15]. Computer anxiety within e-learning environments specifically affects self-efficacy, suggesting a link between anxiety and learning outcomes for both learners and educators [16]. This highlights the importance of self-efficacy in online learning contexts.

Studies such as [17] examined teachers' attitudes towards e-learning during the COVID-19 pandemic, shedding light on the potential development of generalized anxiety disorder among educators. Additionally, [15] emphasized the significance of educators' preparedness for online teaching and its impact on their levels of anxiety, highlighting the need for targeted interventions and support mechanisms to address e-learning-related anxiety among teachers. Further studies by [18] focused on social anxiety in digital learning environments and identified it as a significant challenge for both learners and teaching staff in higher education settings. Similarly, [19] highlights the negative impact of e-learning computer anxiety on adoption rates in higher education, emphasizing the need to address anxiety concerns within online education.

According to [20], gaining insight into how educators manage online learning anxiety is crucial for developing e-learning systems. For example, a study by [21] discovered that anxiety levels changed during different stages of e-learning. E-learning factors such as interface design features, instructional strategies, and students' interactions with each other made learners more or less anxious. Poorly designed interfaces or ambiguous instructions may heighten learner anxiety, whereas interactive features and supportive social networks can mitigate anxiety and enhance engagement [21].

Within the Ghanaian context, self-efficacy is a key factor influencing e-learning adoption and significantly influences individuals' behavioural intentions to use e-learning systems [22]. Research by [23] provides further support, emphasizing that "perceived usefulness and perceived ease of use had a high overall effect... self-efficacy and technological complexity influenced the teachers' intentions to adopt Moodle" (p1). These findings align with those of [24], who argue that teacher perceptions, attitudes, and technological competencies heavily influence the integration of technology into curricula and pedagogy. When teachers lack technological competence, it can lead to technology anxiety. Self-efficacy in education refers to a teacher's belief in their ability to positively influence student outcomes [25]. When self-efficacy is lacking, educators may experience emotional and behavioural challenges that hinder their professional efficacy. Lecturers are agents of change; their lack of self-confidence in using technology can negatively impact delivery. By identifying and mitigating cloud computing e-learning anxiety-related barriers, stakeholders can promote a more conducive environment for practical computer usage and technology integration in various education sectors.

2.1 Learning theories

Learning theories play a crucial role in shaping educational practices and understanding the learning process. They provide a foundational framework for developing effective e-learning practices [26]. Constructivism, behaviourism, cognitivism, and connectivism are among the theories that provide valuable insights into the learning process and can be strategically integrated to enhance e-learning design [26]. These theories guide the development of e-learning environments and instructional strategies that cater to diverse student needs and ultimately improve learning outcomes.

Constructivism, emphasizing active knowledge construction by learners [27], aligns well with e-learning environments. It fosters collaborative activities, diverse perspectives, real-world application, self-reflection, and varied knowledge representation [27]. These elements, integrated into e-learning platforms, can promote cognitive development through diverse learning models and activities [28], ultimately transforming knowledge acquisition.

By incorporating constructivist learning models and discovery learning elements, e-learning structures can cater to individual needs and promote self-directed learning [29]. This approach fosters engaging environments [30], emphasizing the dynamic and social nature of knowledge construction [30], [31]. This social aspect is crucial for e-learning security and fostering a sense of community to address competitive pressures [31].

Besides constructivism, other learning theories can inform e-learning design. Behaviourism, a psychological theory, emphasizes the impact of factors such as attitude, subjective norms, and behavioural control on learners' intentions to use e-learning platforms [32]. Studies by [33] and [13] investigating e-learning adoption in higher education further emphasize the influence of anxiety, perceived usefulness, security, and competitive pressures on learners' decisions.

Cognitivism, another prominent learning theory, focuses on the cognitive processes involved in learning, such as problem-solving, memory, and information processing [34]. Understanding these cognitive processes, as well as how learners perceive and integrate new information, is critical for designing effective e-learning experiences. Integrating cognitive learning strategies into e-learning design can enhance critical thinking, problem-solving abilities, and knowledge retention [35]. A study by [34] emphasizes the importance of understanding learner anxiety and the perceived complexity associated with e-learning environments from a cognitive perspective. Additionally, [36] investigates the relationship between nursing students' anxiety levels and e-learning during the COVID-19 pandemic, providing valuable insights into the impact of cognitivism on anxiety and security in online educational settings.

Another prominent learning theory is connectivism. This learning theory complements constructivism in e-learning by emphasizing the importance of connections between learners and information sources [37], [38]. This theory posits learning as a networked process shaped by technology and social interaction, particularly relevant in massive open online courses (MOOCs) [39]. Connectivism addresses e-learning complexity by equipping learners with tools to navigate diverse resources [40]. While the study does not explicitly address security concerns, its emphasis on networked learning and information exchange underscores the importance of secure platforms for institutions [41]. Furthermore, connectivism fosters active participation, aiding learners in adapting to competitive pressures [38], [39].

Various factors, including technical features, institutional readiness, pedagogical strategies, and diversity, shape the complexity of e-learning. A study by [42] highlights that complexity significantly influences user attitudes towards e-learning adoption. Additionally, security in e-learning, including the protection of sensitive data, ensuring user privacy, preventing unauthorized access, and enabling the smooth operation of online educational activities, is a crucial determinant. Many studies have emphasized the pivotal role of e-learning security in influencing adoption and user satisfaction. E-learning presents benefits such as flexibility, interactivity, and efficiency, ultimately contributing to its cost-effectiveness and accessibility, as observed by [43].

However, there is pressure on teachers in tertiary institutions to implement e-learning, thereby prompting educational institutions, organizations, and individuals to strategically adapt to the competitive demands of the e-learning landscape. [44] affirms that competitive pressure stands as a pivotal factor in e-learning adoption. Understanding these factors is critical for successfully implementing cloud-based e-learning systems. Therefore, the study was guided by the following study questions:

- **i)** *To what extent does cloud computing e-learning adoption anxiety prevail among lecturers in a virtual environment?*
- **ii)** *Does competitive pressure on lecturers mediate the relationship between cloud computing e-learning usefulness, cloud computing e-learning security, and lecturers' e-learning adoption in a virtual environment?*
- **iii)** *How does cloud computing e-learning anxiety moderate the relationship between the investigated factors and lecturers' cloud computing e-learning adoption in a virtual environment?*

3 MATERIALS AND METHODS

3.1 Conceptual framework and hypotheses development

According to the literature review, Figure 1 depicts the conceptual framework used in this study. In this framework, cloud computing e-learning anxiety (ANX), cloud computing e-learning complexity (CPX), cloud computing e-learning security (CCES), cloud computing e-learning usefulness (CCEU), and competitive pressure on lecturers (CPoL) influence lecturers' adoption intentions of cloud computing e-learning (LEAI). Cloud computing e-learning anxiety (ANX) is a moderator variable, while competitive pressure on lecturers (CPoL) is a mediator variable.

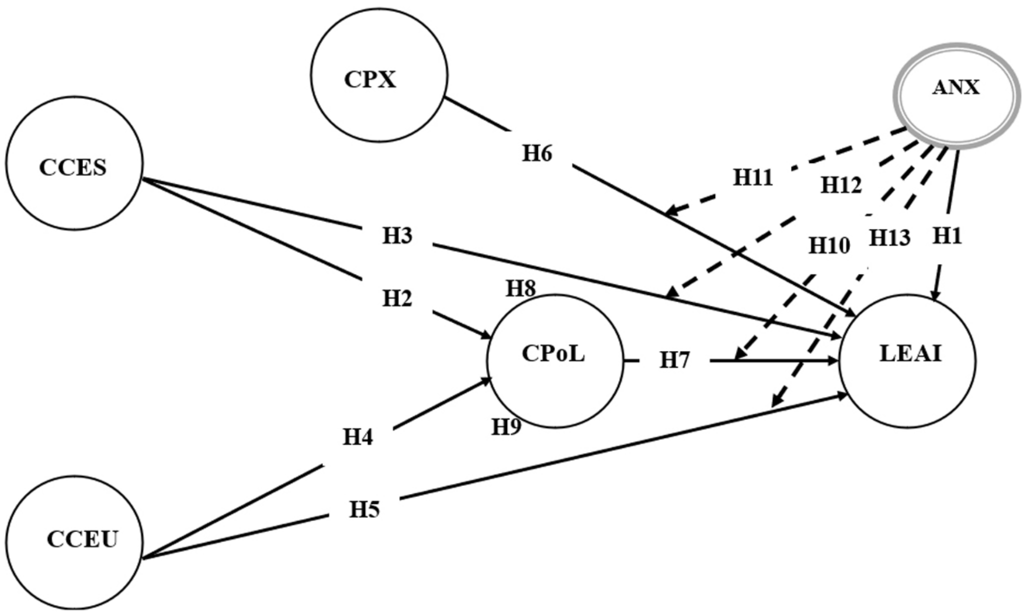

Fig. 1. Proposed PLS-SEM research model for cloud e-learning adoption

Source: Author's own image.

We provide a definition of the factors considered in this study.

1. CCEU: This factor measures how useful lecturers find cloud computing in their e-learning practices.
2. CPoL: This factor measures the extent to which lecturers feel pressured to adopt cloud computing due to competition.
3. CCES: This factor assesses the security aspect of cloud computing e-learning. Strong security measures are essential for lecturers to trust and adopt cloud-based solutions.
4. CPX: This factor evaluates how complex lecturers find the cloud computing e-learning systems.
5. ANX: This measures the level of anxiety lecturers feel towards using cloud computing e-learning.
6. LEAI: This is the outcome variable, representing the intention of lecturers to adopt cloud computing in their e-learning practices.
   We proposed the following hypotheses for the study
   i) **H1:** ANX *significantly influences* LEAI.
   ii) **H2:** CCES *significantly influences* CPoL.
   iii) **H3:** CCES *significantly influences* LEAI.
   iv) **H4:** *CCEU significantly influences* CPoL.
   v) **H5:** CCEU *significantly influences* LEAI.
   vi) **H6:** CPX *significantly influences* LEAI.
   vii) **H7:** CPoL *significantly influences* LEAI.
7. The following hypotheses for mediation analysis were also formulated to examine CPoL's interaction with CCEU and CCES:
   viii) **H8:** CPoL significantly mediates the relationship between CCEU and LEAI.
   ix) **H9:** CPoL significantly mediates the relationship between CCES *and* LEAI.
8. With the moderation analysis, we looked at how ANX interacts with other factors to influence the outcome (LEAI).
   x) **H10:** ANX moderates the relationship between CPoL and LEAI.
   xi) **H11:** ANX moderates the relationship between CPX and LEAI.
   xii) **H12:** ANX moderates the relationship between CCES and LEAI.
   xiii) **H13:** ANX moderates the relationship between CCEU and LEAI.

3.2 Methodology

This study employed a cross-sectional survey design to gather data on each variable in the model from the participants. The data was coded using IBM SPSS (version 27), and the partial least squares structural equation modelling (PLS-SEM) software SmartPLS 4 assessed the study model. We chose this approach because it is suitable for complex models with non-normal data, a common scenario in social science study [45]. Thirteen (13) hypotheses (H1–H13) were examined to investigate both direct and indirect effects within the model. Path analysis was used to explore the mediating role of competitive pressure on the relationships between cloud computing e-learning security, cloud computing e-learning usefulness, and lecturers' adoption intentions. Additionally, we investigated the moderating effect of anxiety (ANX) on these relationships using the capabilities of PLS-SEM in this area. In conclusion, three study questions guided this study.

3.3 The research participants

We invited lecturers from Ghana's ten technical universities to participate voluntarily in our study through their local executives, assuring them of the confidentiality of their data. A total of 1,395 lecturers participated in the study. Table 1 presents a detailed breakdown of participant demographics, including gender, age, education level, teaching rank, length of service, and cloud computing knowledge.

The faculty members exhibited a diverse range of age groups, with the majority falling within the 30 to 40-year age bracket (47%) followed closely by the 41 to 50-year age group (34.2%). The distribution of the remaining participants was relatively evenly between those under 30 (6%) and those over 60 (2.5%), indicating the inclusivity of the sample. In terms of educational attainment, most faculty members held a master's degree (79.1%). A smaller proportion possessed bachelor's degrees (4.5%) or doctorate/DTech degrees (16.4%). Senior lecturers (45.8%) and assistant lecturers (45.5%) comprised the bulk of the teaching ranks. Instructors (6.2%) and professors (2.5%) made up the remaining participants.

Table 1. Demographic information distribution

Descriptives	Number	%
Gender		
Male	853	67.8
Female	405	32.2
	1258	100
Age		
Less than 30 years	76	6
30–40 year	591	47
41–50 years	430	34.2
51–60 years	130	10.3
Above 60 years	31	2.5
Education Level		
Bachelors	57	4.5
Masters	995	79.1
PhD/DTech	206	16.4
Teaching Rank		
Instructor	77	6.2
Assis/Lecturer	573	45.5
Senior Lecturer	576	45.8
Professor	32	2.5
Length of Service		
Less than 5 years	234	18.6
5–10 years	363	28.9
11–15 years	382	30.4
More than 15 years	279	22.2

(Continued)

Table 1. Demographic information distribution *(Continued)*

Descriptives	Number	%
Knowledge of Cloud Computing	**Number**	**%**
Low	612	48.6
High	646	51.4

The faculty members have a relatively balanced distribution of length of service, with about a quarter of them having less than five years (18.6%), 5–10 years (28.9%), 11–15 years (30.4%), or more than 15 years (22.2%) of experience. The faculty members who have a slightly higher knowledge of cloud computing (51.4%) are more knowledgeable than those with low knowledge (48.6%).

3.4 Research instrument

The data collection tool used was a closed-ended questionnaire with two parts. The first part collected data regarding participants' demographic characteristics, while the second part captured the participants' responses to 29 different items, which measured six key variables related to cloud computing e-learning anxiety and adoption behaviours. The items in the questionnaire were rated on a five-point Likert-type scale, with 1 being "Strongly Disagree" and 5 being "Strongly Agree." This questionnaire was developed based on previous studies by [46–50] and was modified based on the findings of a literature review. A panel of experts from the Cape Coast Technical University Computer Science and Technology department verified the instrument's validity and reliability by incorporating changes to the questionnaire.

3.5 Data collection procedures

To facilitate participation, the study team conducted introductory sessions at all ten Ghanaian technical universities. These sessions provided detailed explanations of the study's objectives and the significance of participant involvement. After these sessions, we initiated a systematic data collection process, focusing on the 1,778 active members of the Technical University Teachers' Association of Ghana (TUTAG). This approach ensured participants were well-informed about the study's goals and their role in its success. A total of 1,395 faculty members participated in the data collection process by completing the questionnaires. In the end, we retrieved 1,258 completed questionnaires, indicating an impressive response rate of 90.2%.

3.6 Data analysis

The participants' questionnaire responses were coded using IBM SPSS Statistics version 27 [51]. Prior to conducting the primary analysis, the raw data were examined for missing values. We addressed the missing data using Little's multivariate test for missing completely at random (MCAR) and expectation-maximization (EM) algorithm techniques. Descriptive statistics were generated to characterize the collected data. These statistics included measures of central tendency (mean) and dispersion ((SD) standard deviation, variance), as well as measures of normality (skewness and kurtosis). PLS-SEM with SmartPLS 4 software [52] was utilized to assess the measurement model's properties. SmartPLS 4 is a variance-based SEM technique well-suited for analysing complex structural models, particularly those including formative constructs. As highlighted by [45, p. 5], "PLS-SEM can be used when the path model includes formatively measured constructs and requires latent variable scores for follow-up analyses." This evaluation focused on the external loadings, indicator reliability, composite reliability, and average variance extracted (AVE) of the constructs within the model. Following the validation of the measurement model, path analysis was conducted using PLS-SEM to assess the hypothesized relationships (H1–H13) within the structural model. This comprehensive evaluation allowed for the investigation of the study questions that guided the study.

4 RESULTS

4.1 Descriptive statistics of the variables

Table 2 presents the descriptive statistics analysis of participants' cloud computing e-learning adoption and anxiety. Table 2 shows that the mean values of all factors range from 3.154 to 3.938, indicating that lecturers' average responses for all variables are around 3, the middle point of the Likert scale.

All groups' SD and variance values are also very similar, ranging from 0.793 to 1.268 for SD and 0.629 to 1.607 for variance. These findings suggest relatively low variability or diversity in the lecturers' responses for all variables. The data predominantly clusters around the mean, suggesting a consistent or homogeneous perception of all the variables by the lecturers.

Table 2. Descriptive statistics of the distribution

Construct	Items	Min	Max	Mean	SD	Variance	Skewness	Kurtosis
ANX	ANX1	1	5	3.293	1.154	1.332	–0.244	–1.220
	ANX2	1	5	3.641	1.201	1.443	–0.557	–0.948
	ANX3	1	5	3.264	1.268	1.607	–0.181	–1.323
	ANX4	1	5	3.154	1.159	1.343	–0.082	–1.277
LEAI	LICCE1	1	5	3.605	1.009	1.017	–0.854	–0.006
	LICCE2	1	5	3.313	1.157	1.339	–0.516	–0.883
	LICCE3	1	5	3.692	1.177	1.385	–0.840	–0.231
	LICCE4	1	5	3.636	1.067	1.139	–1.093	0.487
	LICCE5	1	5	3.654	1.083	1.173	–1.027	0.346
CPX	CPX1	1	5	3.585	1.102	1.215	–0.982	0.075
	CPX2	1	5	3.581	1.015	1.031	–0.967	0.158
	CPX3	1	5	3.612	1.167	1.363	–0.643	–0.525
	CPX4	1	5	3.532	1.168	1.365	–0.828	–0.311
	CPX5	1	5	3.520	1.155	1.335	–0.755	–0.326

(Continued)

Table 2. Descriptive statistics of the distribution *(Continued)*

Construct	Items	Min	Max	Mean	SD	Variance	Skewness	Kurtosis
CCEU	CeU1	1	5	3.866	1.018	1.035	–1.083	0.705
	CeU2	1	5	3.860	1.000	1.000	–1.156	0.922
	CeU3	1	5	3.731	1.031	1.062	–1.113	0.726
	CeU4	1	5	3.896	0.991	0.983	–1.233	1.313
	CeU5	1	5	3.751	0.971	0.943	–0.969	0.617
CCES	CeS1	1	5	3.938	0.819	0.671	–1.252	2.071
	CeS2	1	5	3.630	1.073	1.151	–0.853	–0.053
	CeS3	1	5	3.703	1.032	1.065	–1.056	0.489
	CeS4	1	5	3.548	1.040	1.082	–0.848	–0.083
	CeS5	1	5	3.630	1.070	1.145	–0.743	–0.355
CPoL	CPoL1	1	5	3.885	0.793	0.629	–1.058	1.811
	CPoL2	1	5	3.633	0.992	0.984	–0.934	0.254
	CPoL3	1	5	3.909	1.022	1.043	–0.935	0.076
	CPoL4	1	5	3.926	0.984	0.967	–0.937	0.262
	CPoL5	1	5	3.827	0.912	0.832	–1.055	0.973

Note: No of participants (N) = 1258, missing values = 0.

All the groups have negative skewness values, ranging from –1.252 to –0.082, indicating a leftward or negatively skewed response from the lecturers for all variables. This indicates that there are more responses above than below the mean. All groups' kurtosis values are negative, ranging from –1.323 to –2.071, indicating that the distributions of the lecturers' responses for all variables are platykurtic or have lower kurtosis than the normal distribution. As a result, the distributions are flat or have thin tails, and there are fewer outliers or extreme values than the normal distribution. There are no significant variances from the mean, indicating that the lecturers have reactions comparable to one another or consistent in degree.

4.2 Lecturers cloud computing e-learning adoption anxiety

Table 3 displays the frequency and percentage distributions of faculty members' agreement levels, along with four statements related to their cloud computing e-learning adoption anxiety. This analysis addresses the initial study question regarding the level of anxiety among the participants.

The findings reveal a moderate to high level of anxiety among faculty members concerning cloud computing e-learning adoption. A significant portion of respondents agreed or strongly agreed with the statements presented. The statement "I might unintentionally make mistakes while using cloud computing e-learning technology" garnered the highest level of agreement (67%) and the highest mean score (3.64), suggesting this particular concern is most prevalent. Conversely, the statement "Using cloud computing e-learning technology makes me nervous or apprehensive" received the lowest level of agreement (56.2%) and a mean score of 3.38. Similarly, the statement "I am hesitant to adopt cloud computing e-learning because it requires people to correct mistakes" exhibited a lower level of agreement (54.7%) and a mean score of 3.21. While the statement "I find cloud computing e-learning technologies to be quite frightening or scary" received the lowest mean score (3.15), indicating a lesser degree of agreement (50%), the corresponding disagreement rate (40.3%) was also the lowest. This suggests a more nuanced perception of fear among faculty members, with a notable portion (40.3%) still experiencing some level of fear.

Table 3. Cloud e-learning adoption anxiety among lecturers

Items	SD		D		N		A		SA		M	SD
Adoption Anxiety	No	%	No	%	No	%	No	%	No	%		
Using cloud computing e-learning technology makes me nervous or apprehensive.	49	3.9	400	31.8	102	8.1	547	43.5	160	12.7	3.29	1.15
The idea that I might unintentionally make mistakes while using cloud computing e-learning technology bothers me.	42	3.3	294	23.4	80	6.4	500	39.7	342	27.2	3.64	1.2
I am hesitant to adopt cloud computing e-learning because it requires people to correct mistakes.	85	6.8	410	32.6	74	5.9	466	37.0	223	17.7	3.27	1.27
I find cloud computing e-learning technologies to be quite frightening/scary.	61	4.8	446	35.5	122	9.7	496	39.4	133	10.6	3.15	1.16

Note: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree, M = Mean.

The study reveals that some faculty members are neutral, with the highest level of neutrality found when they find cloud computing and e-learning technologies frightening or scary (9.7%). The majority also feel nervous or apprehensive (8.1%), worried about unintentional mistakes (6.4%), and hesitant (5.9%). The standard deviation values associated with these statements suggest a moderate level of variation in agreement among participants. The statement "I am hesitant to adopt cloud computing e-learning because it requires people to correct mistakes" exhibited the highest standard deviation (1.27), indicating a greater spread of opinions on this particular concern. Conversely, the statement "Using cloud computing e-learning technology makes me nervous or apprehensive" exhibited the lowest standard deviation (1.15), suggesting a more consistent level of nervousness or apprehension among faculty members.

4.3 Assessment of the measurement models

We assessed the validity and reliability of the measurement model for our constructs and dimensions. Following the recommendations by [53], we assessed the indicators' loadings, internal consistency reliability, and convergent and discriminant validity. [53] recommend that indicator loadings above 0.708 be considered acceptable, indicating that the construct explains over 50% of the indicator's variance. We removed eight indicators with lower loadings based on this criterion. However, six indicators with loadings slightly below 0.7 were retained, as suggested by [53], because their removal did not improve internal consistency and reliability.

Traditionally, Cronbach's alpha has been used to assess internal consistency and reliability, with 0.7 as the minimum acceptable value. Recent studies [45] suggest that Cronbach's alpha may underestimate reliability; therefore, internal consistency reliability was assessed using composite reliability (CR). All CR values exceeded the recommended range of 0.6 to 0.7 [53], indicating acceptable internal consistency. However, according to [54], values exceeding 0.95 could suggest redundant items, which could potentially compromise construct validity. Convergent validity was assessed through average variance extracted (AVE). From Table 4, the AVE values range from 0.506 to 0.566, exceeding the 0.5 threshold proposed by [55]. This result suggests satisfactory convergent validity, indicating a good correlation between indicators and their underlying latent variables.

Table 4. Internal consistency measures for the measurement model

Latent Variable	Indicators	Loadings	Indicator Reliability	Composite Reliability	AVE
CPX	CCC2	0.777	0.603	0.771	0.533
	CCC3	0.802	0.643		
	CCC4	0.595	0.354		
CCES	CCeS2	0.686	0.471	0.812	0.520
	CCeS3	0.769	0.591		
	CCeS4	0.710	0.504		
	CCeS5	0.716	0.512		
CPoL	CPTU3	0.783	0.614	0.796	0.566
	CPTU4	0.726	0.527		
	CPTU5	0.746	0.556		
ANX	LCCUA1	0.817	0.667	0.825	0.542
	LCCUA2	0.644	0.415		
	LCCUA3	0.746	0.556		
	LCCUA4	0.728	0.530		
LEAI	LICCE1	0.670	0.449	0.817	0.528
	LICCE2	0.711	0.506		
	LICCE4	0.775	0.601		
	LICCE5	0.746	0.556		
CCEU	UCCeT2	0.752	0.566	0.803	0.506
	UCCeT3	0.650	0.423		
	UCCeT4	0.686	0.470		
	UCCeT5	0.752	0.565		

According to [56] and [55], recent study has highlighted limitations in Fornell and Larcker's 1981 [57] metric for assessing discriminant validity due to potential reliability issues. As an alternative, the heterotrait-monotrait ratio (HTMT) is now commonly used to evaluate discriminant validity in structural equation modelling (SEM).

Consequently, this study employed the HTMT to evaluate the distinctiveness of the constructs within the structural equation model [53]. The HTMT values should be less than 0.9, as suggested by [56] and [58]. Table 5 presents the results, indicating that all constructs exhibit distinctiveness, with the upper values of the 97.5% confidence intervals below 0.85.

Table 5. The HTMT ratios and their confidence intervals

Paths	HTMT	CI (2.5%)	CI (97.5%)
CCES <–> ANX	0.184	0.142	0.246
CCEU <–> ANX	0.353	0.279	0.428
CCEU <–> CCES	0.406	0.315	0.492
CPX <–> ANX	0.196	0.167	0.264
CPX <–> CCES	0.309	0.230	0.410
CPX <–> CCEU	0.320	0.225	0.430
CPoL <–> ANX	0.231	0.189	0.292
CPoL <–> CCES	0.402	0.304	0.493
CPoL <–> CCEU	0.414	0.327	0.505
CPoL <–> CPX	0.299	0.210	0.404
LEAI <–> ANX	0.396	0.330	0.464
LEAI <–> CCES	0.347	0.259	0.431
LEAI <–> CCEU	0.378	0.304	0.462
LEAI <–> CPX	0.370	0.276	0.468
LEAI <–> CPoL	0.388	0.302	0.479

Note: CI = Confidence Intervals.

4.4 Assessing the structural model

A potential concern in formative measurement models is multicollinearity, which can arise when predictor variables exhibit high correlations. This study addressed multicollinearity by examining path coefficients, their significance, and the coefficient of determination (R^2) values [59]. We assessed multicollinearity using the variance inflation factor (VIF). While [60] suggested a VIF threshold of 3.3, [53] recommended a value of "approximately three (3) or lower" (p. 147).

As shown in Table 6, the VIF values in this study range from 1.055 to 1.213, well below the recommended threshold. These findings support the absence of multicollinearity and ensure the unbiased interpretation of path coefficients. The assessment of the model indicates that the combined influence of all exogenous latent variables (ANX, CPX, CCES, and CCEU) and the endogenous factor (CPoL) moderately accounts for 21.1% of the variance in lecturers' adoption intentions of cloud computing e-learning (LEAI) in a virtual environment. This finding suggests that the proposed model provides a meaningful explanation for lecturers' adoption behaviour, although there may be other unobserved factors influencing their decisions.

Table 6. The details of the evaluation of the structural model

Hypothesis	Path	β	t	p	f^2	95% Confidence Intervals	Sig	VIF
H1	ANX –> LEAI	0.241	10.136	0.000	0.070	[0.196, 0.289]	Yes	1.055
H2	CCES –> CPoL	0.209	6.374	0.000	0.045	[0.144, 0.272]	Yes	1.084
H3	CCES –> LEAI	0.131	4.593	0.000	0.019	[0.075, 0.187]	Yes	1.145
H4	CCEU –> CPoL	0.213	6.344	0.000	0.047	[0.148, 0.279]	Yes	1.084
H5	CCEU –> LEAI	0.105	3.400	0.001	0.012	[0.043, 0.166]	Yes	1.213
H6	CPX –> LEAI	0.151	5.470	0.000	0.027	[0.101, 0.210]	Yes	1.075
H7	CPoL –> LEAI	0.167	5.335	0.000	0.031	[0.106, 0.230]	Yes	1.144
Mediation (Indirect Paths)								
H8	CCES –> CPoL –> LEAI	0.035	3.798	0.000		[0.019, 0.055]	Yes	
H9	CCEU –> CPoL –> LEAI	0.036	4.109	0.000		[0.020, 0.055]	Yes	

Notes: β = path coefficient. Significance (sig), $p < 0.05$.

4.5 Test of hypothesis

To assess the hypothesized relationships within the structural model, a bootstrapping procedure with 5,000 resamples was employed. We checked path coefficient (β) values for statistical significance at a 5% alpha level to see how well the model could explain both direct and indirect effects on the outcome variable, which was lecturers' intention to adopt e-learning (LEAI). Table 6 presents the detailed results, while Figure 2 provides a visual representation of the significant paths. The findings reveal that all seven hypothesized direct relationships (H1–H7) were statistically significant ($p \leq 0.001$), with confidence intervals excluding zero, suggesting that they significantly influence the outcome variable LEAI. The coefficient values for the significant direct paths range from 0.105 to 0.241. Additionally, f^2 values range from 0.012 to 0.070, suggesting small to medium effects for all significant predictions [53] and [61]. Based on the analysis of f^2, p-values, and t-values, the relationship between cloud computing e-learning anxiety (ANX) and LEAI (H1) emerges as the most impactful ($\beta = 0.241$, $t = 10.136$, $p < 0.001$). This finding highlights the importance of addressing anxiety-related barriers, as ANX explains approximately 7% of the variance in LEAI ($f^2 = 0.070$). On the other hand, the link between cloud computing e-learning usefulness (CCEU) and LEAI (H5) has the smallest effect size ($\beta = 0.105$, $t = 3.400$, $p = 0.001$), explaining only 1.2% of the variation in LEAI ($f^2 = 0.012$). Conversely, the relationship between cloud computing e-learning usefulness (CCEU) and LEAI (H5) exhibits the smallest effect size ($\beta = 0.105$, $t = 3.400$, $p = 0.001$), explaining only 1.2% of the variance in LEAI ($f^2 = 0.012$).

4.6 Mediation analysis

We conducted a mediation analysis to address our second study question. Considering both hypotheses (H8 and H9), it is evident that there is a significant mediating effect, as shown in Table 6 and Figure 2. The positive values, large t-values, very low p-values, and narrow confidence intervals reveal a significant mediating effect.

H8: ($\beta = 0.035$), ($t = 3.798$), ($p < 0.001$), 95% CI [0.019, 0.055].
H9: ($\beta = 0.036$), ($t = 4.109$), ($p < 0.001$), 95% CI [0.020, 0.055].

The mediation analysis underscores the significance of competitive pressure as a mediator in adopting cloud computing in e-learning. These findings highlight the importance of considering competitive pressure as a mechanism influencing faculty decisions to adopt cloud-based e-learning technologies.

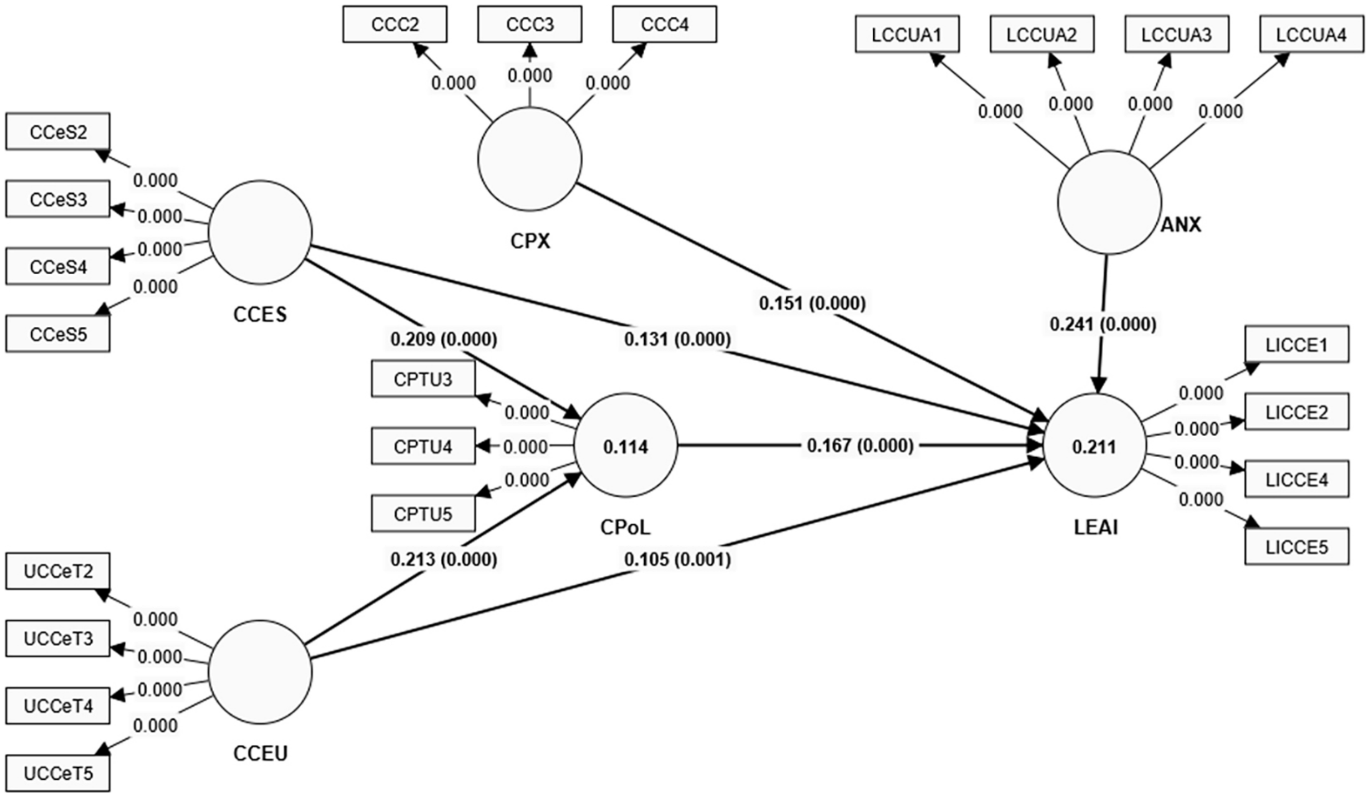

Fig. 2. The structural model showing both path coefficients and the p-values in a bracket
Source: Authors image generated from SmartPLS 4.

4.7 Moderation analysis

The third study question explored the potential moderating effect of cloud computing e-learning anxiety (ANX) on the relationships between the independent variables CPoL, CPX, CCES, and CCEU and the dependent variable, LEAI (i.e., hypotheses H10–H13). A moderation analysis was conducted to examine this interaction effect. Table 7 presents the results of the moderation analysis. Non-significant p-values (0.731 and 0.305, respectively) indicated the lack of support for hypotheses H10 and H13, leading to the rejection of both hypotheses.

Table 7. Moderation analysis

Hypothesis	Path	β	t	p	f^2	R^2 Before Inclusion of MD	R^2 After Inclusion of MDI	Decision
H10	ANX x CPoL –> LEAI	–0.008	0.344	0.731	0.001	21.10%	–	Rejected
H11	ANX x CPX –> LEAI	–0.059	2.603	0.009	0.006		**0.216 21.6%**	Accepted
H12	ANX x CCES –> LEAI	–0.058	2.554	0.011	0.005		**0.215 21.5%**	Accepted
H13	ANX x CCEU –> LEAI	–0.024	1.027	0.305	0.001		–	Rejected

Notes: β = path coefficient, Significance (sig), $p < 0.05$, MDI = moderation interaction.

In contrast to H10 and H13, the findings for hypotheses H11 and H12 revealed statistically significant negative moderation effects. This is evidenced by the negative beta (β) coefficients of –0.059 (H11) and –0.058 (H12) in Table 7. A negative moderation effect indicates that ANX weakens the positive relationships between CPX and LEAI (H11), as well as between CCES and LEAI (H12). The interaction effect sizes (f^2) were examined. The f^2 values of 0.006 for H11 and 0.005 for H12 suggest that ANX has a small but measurable impact on the relationships between CPX and LEAI and CCES and LEAI, respectively [53]. While these effects are statistically significant, they are relatively small, indicating a limited moderating influence of anxiety. The changes in R-squared values for the dependent variable (LEAI) further support this limited moderating effect. For H11, the LEAI R^2 was 0.211 without the interaction term (ANX x CPX). Including it raised the LEAI R^2 to 0.216, meaning the dependent variable (LEAI) accounted for an additional 0.5% of the variance, signifying a minor change in interaction. Similarly, for H12, incorporating the moderating effect (ANX x CCES) increased the R^2 value for LEAI from 0.211 to 0.215, reflecting a 0.4% rise in variance explained by LEAI, which is also a relatively small interaction change.

5 DISCUSSIONS

To address our first study question, a survey instrument measured lecturers' agreement with four statements reflecting concerns about adopting cloud computing e-learning technologies. The findings conclusively revealed a moderate level of anxiety among faculty members at the technical universities regarding the adoption of these technologies. The primary cause of this anxiety is the fear of making unintentional mistakes, with 67% of faculty members expressing this concern and giving it an average rating of 3.64. This result is consistent with prior study by [62] and [63], which suggests that anxiety can impede users' willingness to adopt and integrate new technological innovations.

The analysis of our proposed framework demonstrates significant explanatory power, accounting for 21.1% of the variance in lecturers' adoption intentions of cloud computing e-learning technologies within a virtual environment. According to [64], a model explaining 21.1% of the variation in the dependent variable is considered satisfactory, as R^2 values in social science study typically range from 0.10 to 0.50. Furthermore, [53] and [65] suggest that the contextual interpretation of R^2 values depends on the study domain and the number of predictor constructs employed. The findings of this study align with the conclusions of [66] and [67]. These studies highlight that perceived usefulness, trust, complexity, and security significantly influence individuals' willingness to engage with e-learning virtual platforms.

Path analyses were conducted to explore the mediating effect of competitive pressure on lecturers (CPoL) and the relationship between cloud computing e-learning security (CCES) and lecturers' adoption intentions. The results revealed a significant mediation effect. Lecturers who see cloud computing e-learning technologies or virtual environments as secure are more likely to sense pressure to adopt them due to increased competition. The improved security of these tools enhances their confidence in using them to safeguard data and interactions. Consequently, robust security measures undeniably strengthen the adoption of cloud computing e-learning by intensifying the competitive environment in which lecturers operate.

Likewise, the influence of competitive pressure on lecturers is a significant mediator in the relationship between the usefulness of cloud computing e-learning and lecturers' intentions to adopt e-learning. This implies that lecturers who consider cloud e-learning virtual environment tools highly beneficial face heightened competitive pressure. An extra driving force stems from the practical advantages, such as increased accessibility to educational resources and strengthened collaboration. This finding is consistent with earlier studies on the adoption of e-learning, which also take into consideration factors such as security, usefulness, and competitive pressure. [43], [68] Lecturers should adopt cloud computing e-learning in a virtual environment to align themselves with their peers, who are already capitalizing on these tools.

Our exploration of the moderating role of ANX yielded mixed results. Hypotheses H10 and H13 were rejected, while H11 and H12 were supported. This underscores the complex interplay of factors influencing faculty adoption intentions. The study's findings revealed that e-learning anxiety does not moderate the relationships between competitive pressure, e-learning usefulness, and lecturers' adoption intentions. These results suggest that, while e-learning anxiety is an important consideration, it may not substantially impact how competitive pressure and the perceived usefulness of cloud computing influence adoption decisions.

However, ANX significantly moderates the relationships between perceived complexity, security, and lecturers' adoption intentions. This suggests that lecturers' anxiety levels influence their perception and response to the complexity of cloud e-learning environments. Lecturers with higher anxiety perceive these environments as more complex, hindering their adoption. Conversely, lower anxiety is associated with perceiving the complexity as manageable and fostering adoption.

These findings unequivocally support the study conducted by [69], emphasizing a clear correlation between teachers' anxiety levels and their acceptance of e-learning. This underscores the crucial importance of prioritizing their psychological well-being. Similarly, [70] and [71] have confidently highlighted anxiety as a significant factor influencing teachers' attitudes and experiences with e-learning. Therefore, possessing a comprehensive understanding of and proactively addressing anxiety levels among lecturers is essential for confidently promoting the adoption of cloud computing e-learning in virtual environments.

6 CONCLUSIONS

This study aimed to investigate the anxiety levels of lecturers at technical universities in Ghana regarding e-learning adoption, as well as the mediating role of CPoL among key adoption factors. Additionally, we examined the moderating role of ANX on lecturers' e-learning adoption intentions based on the factors under study. We guided the study with the following study questions:

i) To what extent does cloud computing e-learning adoption anxiety prevail among lecturers in a virtual environment?
ii) Does competitive pressure on lecturers mediate the relationship between cloud computing e-learning usefulness, cloud computing e-learning security, and lecturers' e-learning adoption in a virtual environment?
iii) How does cloud computing e-learning anxiety moderate the relationship between the investigated factors and lecturers' cloud computing e-learning?

This study employed a quantitative study design using PLS-SEM with SmartPLS software. A comprehensive survey was administered to 1,395 lecturers across 10 Ghanaian technical universities, yielding a high response rate of 90.2% (n = 1,258). The analysis examined the hypothesised model, including direct, indirect, mediating, and moderating effects among the variables, to address the study's 13 hypotheses and 3 study questions.

In response to the study's study questions, the study identified moderate anxiety among lecturers regarding cloud computing e-learning in a virtual environment, with fear of mistakes as a key concern. The findings also demonstrated that competitive pressure emerged as a significant mediator between cloud computing e-learning usefulness, security, and lecturers' adoption intentions. The technical universities should prioritize strategies that enhance the usefulness and security of cloud e-learning virtual environments. Finally, we found that, while anxiety did not moderate the relationships between competitive pressure on lecturers, cloud computing e-learning usefulness, and lecturers' adoption intentions, it significantly moderated the relationships between cloud computing e-learning complexity, security, and lecturers' adoption intentions. Lecturers with higher anxiety levels perceive cloud computing e-learning systems as more complex and security features as more critical, potentially influencing their adoption decisions.

Considering these findings, we propose the following recommendations: Regular workshops and training sessions should be implemented for lecturers. A dedicated support team should complement these initiatives to assist with any technical challenges related to cloud e-learning virtual environments. It is crucial to design platforms that are intuitive and user-friendly to alleviate e-learning anxiety. Furthermore, fostering a supportive and competitive environment, as well as providing access to psychological support services, can encourage lecturers to embrace new technologies and uphold their technological proficiency. Finally, the technical universities should prioritize robust security measures within the cloud e-learning virtual environments to alleviate concerns and ensure a safe and secure online learning experience.

Our study presents several intriguing findings and insights; however, it also has certain limitations that must be acknowledged. The study's focus on technical universities and its cross-sectional design limit the generalizability of the findings to lecturers in non-technical settings or private institutions. To improve the generalization of the results, future study should include a broader range of participants from diverse Ghanaian tertiary institutions. The cross-sectional design also hinders the establishment of causal relationships between variables. We recommend longitudinal studies to monitor changes in faculty adoption intentions and anxiety levels over time. While the study explores key factors, it does not cover all aspects of e-learning adoption and anxiety. Future study should investigate additional moderating effects and alternative moderators to gain a deeper understanding of the CCE-learning adoption process.

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