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Examining cloud-based learning in higher education: The role of infrastructure, security, and student trust

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Abstract

The use of cloud computing in education has been shown to positively impact learning, ease the distribution of learning materials, and increase collaboration between students and academic staff. Today, many factors influencing students' use of cloud computing systems have been studied. In this study, we analyzed the roles of these four factors: network quality, service experience, security, and trust. A conceptual model linking these factors together is proposed. The model is tested empirically using PLS-SEM, a method often used for studying complex relationships and prediction models in educational technology adoption. Data were collected through a survey of Computer Science students at the University of Vlora who had experience using cloud platforms for learning. The results show that network quality positively impacts students' service experience. While service experience and security both influence trust in using cloud systems. Also, trust has a strong influence on students' intention to use cloud computing-based learning. The model accounts for 51.9% of the variance in service experience, 66.6% in trust, and 67.4% in intention, indicating substantial explanatory power. Higher education institutions that intend to implement cloud computing systems in teaching should seriously engage in significant investments regarding the quality of the computer network and its security.

Keywords: Cloud-based learning, Higher education, Network quality, PLS-SEM, Security, Service experience, Trust.

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Contribution of this paper to the literature
This study contributes to the existing literature by presenting a framework that explains cloud-based learning adoption through both infrastructural and trust-related factors. The paper's primary contribution is showing that network quality and security influence students' intention to use cloud-based learning by shaping service experience and trust. This study documents the importance of reliable digital infrastructure in higher education.

1. Introduction

Cloud computing technologies have significantly transformed higher education by offering cost-effective and adaptable solutions that improve teaching, research, and administrative tasks. These technologies foster collaboration, boost efficiency, and drive innovation while managing security, cost, and accessibility challenges (Abdasameea, Daduch, & Mawloud, 2025). Digital tools like Google Drive and Microsoft OneDrive allow continuous access to learning resources for both students and educators. This adaptive capacity has sped up the integration of cloud services in today's educational environments. As the educational landscape continues to change, institutions must see digital learning as both a technological advancement and a key strategic goal to improve the overall student experience (Alenezi, 2023).

The COVID-19 pandemic has greatly altered the educational environment, leading to the need for new online teaching approaches. In their study, Carabregu-Vokshi, Ogruk-Maz, Yildirim, Dedaj, and Zeqiri (2024) found that systems that are easy to use, faculty-engaging, and interactive online courses improved students' digital skills and academic results.

As cloud-based learning platforms are increasingly used in higher education, it is important to understand the factors that encourage students to use this technology in learning. According to recent studies, the integration of interactive learning systems in the cloud and mobile increases student participation and supports their academic success (Ahmed, El-Sabagh, & Elbourhamy, 2025; Singh, 2024; Wagino et al., 2024). Wu and Plakhtii (2021) also conclude that cloud computing improves not only student performance but also institutional operations and offers strong data security. In recent years, in the literature, many studies have examined the successful implementation of technology in education using models known as the Unified Theory of Acceptance and Use of Technology (UTAUT) or the Technology Acceptance Model (TAM) (Mohamad, Amron, & Noh, 2021; Sayginer, 2023).

Factors that influence users' willingness to adopt cloud computing technologies in education are usually grouped into three categories: technical, organizational, and user behavioral factors (Chanda, Vafaei-Zadeh, Hanifah, & Ramayah, 2024; Noh & Amron, 2021). According to Mohamad, Amron, and Noh (2021), TAM models focus on ease of use, perceived usability of the system, and ease of understanding of the technology in forming students' intentions to use it. In addition, students' trust in digital learning environments is affected by the security and privacy of the data they share (Anwar, 2021). The effectiveness of e-learning systems has been studied using different models and methods. For example, according to Al-Fraihat, Joy, Masa'deh, and Sinclair (2020), it includes system quality, information quality, service quality, and user-related factors that affect user satisfaction, perceived usefulness, and how often the system is used.

The purpose of our study is to analyze the factors influencing the adoption of cloud-based learning in higher education. Based on a careful review of the literature, we have proposed a conceptual model that integrates these four factors: network quality, service experience, security, and user trust. The relationships between the various factors were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), a method often used to study complex relationships and prediction models in educational technology adaptation systems (Mohamad, Amron, & Noh, 2021; Sayginer, 2023). Combining our factors into a single, integrated framework gives a broader explanation of the adoption of cloud-based learning in higher education.

1.1. Contributions

In this study, we have proposed a model that explains the adoption of cloud-based learning in higher education. To provide a more complete explanation of how these systems are adopted from the students' perspectives, we have integrated four basic factors: network quality, service experience, security, and trust.

The findings of this research contribute to theoretical and practical perspectives. From a theoretical perspective, it helps to better understand the factors that influence the adoption of cloud-based learning in higher education. It also lays the foundation for studies on the factors of cloud computing use in education in the Albanian context. At the same time, tangible results are provided for universities. Higher education institutions should focus more on improving network infrastructure and strengthening security mechanisms to increase student confidence and support the effective use of cloud systems in education.

2. Literature Review

Cloud computing is considered a tool that can improve education systems, especially in developing countries, and increase opportunities for distance learning (Thavi, Jhaveri, Narwane, Gardas, & Jafari Navimipour, 2024). The integration of cloud computing and other digital technologies is necessary for improving academic outcomes and data management in educational institutions. Also, cloud computing is considered an effective solution for supporting personalized and autonomous learning (Matthew, Kazaure, & Okafor, 2021). Traditional e-learning systems require large investments in software and hardware, while cloud computing offers a more economical and flexible alternative. Through cloud-based e-learning, it is possible to have access at any time and from any device, and it offers higher scalability and efficiency (El Mhouti, Erradi, & Nasseh, 2018; Saad, Al Nawaiseh, Helmy, Moawad, & Khali, 2020).

Many factors influence the use of cloud computing in the education environment. Organizational, technological, and institutional factors are crucial for increasing the use of this technology (Amron & Noh, 2021; Thavi et al., 2024). Also, according to Qasem, Abdullah, Jusoh, Atan, and Asadi (2019), the factors influencing the adoption of cloud computing in higher education are both at the individual level (lack of knowledge) and at the organizational level. Successful adoption of cloud computing requires a thorough understanding of technological,

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organizational, and environmental factors, as well as a special focus on information security to maximize benefits in educational institutions (Aldaaja et al., 2025; Isa et al., 2019).

In their study, Amron and Noh (2021) analyze the factors that influence the adoption of cloud computing in higher education institutions using the Technology Acceptance Model (TAM). With PLS-SEM analysis, they concluded that perceived usefulness and perceived ease of use positively and significantly influence the intention to use cloud computing. Meanwhile, safety and learning environment have a positive impact on adoption. Wandira, Fauzi, and Nurahim (2024) also analyzed the adoption of cloud computing in academic systems through SEM-PLS. The main variables of the model were: ease of use, usefulness, facilitating conditions, confirmation, satisfaction, and intention to use. Satisfaction turns out to be the strongest influencing factor, followed by usefulness and ease of use (Wandira, Fauzi, & Nurahim, 2024). According to literature research by Pişirir, Uçar, Chouseinoglou, and Sevgi (2020), it is emphasized that research on cloud computing is dominated by technology adoption analysis and the use of models such as TAM, while the most common dependent variables are adoption, intent to use, and actual use. The main influencing factors include security and privacy, cost, ease of use, risk, and usefulness.

Despite the significant benefits of implementing cloud computing (flexibility, lower cost, higher speed, and efficiency), there are challenges such as cost, bandwidth, security, management, and user acceptance (Alam, 2022). There are many barriers to digital transformation in higher education institutions. These barriers can be grouped into six categories: environmental, strategic, organizational, technological, people-related, and cultural (Gkrimpizi, Peristeras, & Magnisalis, 2023). Among the main factors hindering the adoption of cloud computing in education are security, privacy, and trust, as users have concerns about protecting sensitive data. Higher education institutions, despite the great potential of using cloud computing, have difficulty fully implementing it due to concerns about security and trust (Ali, 2019). According to Onyema, Nwafor, Ugwugbo, Rockson, and Ogbonnaya (2020), security is a critical factor for the adoption of cloud computing in education. To increase trust and use of this technology, it is recommended that cloud providers and institutions continuously improve security mechanisms and address existing and emerging threats. Also, according to the study by Khalid and Zolkipli (2022), security and privacy are critical factors for the adoption of cloud computing in higher education, and the increase in these risks may prevent institutions from adopting this technology without adequate safeguards.

In their study, Samsudeen and Mohamed (2019) used quantitative empirical methodology, based on the UTAUT2 model, and analyzed the adoption of e-learning in Sri Lankan universities through Structural Equation Modeling (SEM). They found that factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, internet experience, and hedonic motivation have a significant impact on the intention and use of e-learning systems. These variables directly affect user behavior and adoption level. Even though there is a lot of research on technology adoption and cloud computing, little attention has been paid to the infrastructure conditions that make or hinder cloud-based learning experiences. Most studies on adoption emphasize how useful or easy a technology is to use, but the reliability of network infrastructure has not been thoroughly explored. This is important because, in learning environments that depend on the cloud, stable internet access is essential for digital services, resource syncing, and real-time collaboration. Without reliable networks, students may face interruptions that affect how they view these platforms. Thus, the gap this study addresses is understanding how the quality of infrastructure, especially network reliability, influences students' trust and adoption of cloud-based learning services. By seeing cloud-based learning adoption as a trust process driven by infrastructure, this study goes beyond traditional acceptance factors to look at how infrastructure, experience, and trust are connected. Although existing studies on technology adoption have provided important contributions, most of them focus on specific dimensions such as technology acceptance models (TAM, UTAUT), system quality, or trust factors. The current literature does not fully address the role of network quality as a fundamental factor influencing user experience, and subsequently the formation of trust and intention to use. Also, an approach that directly connects key elements such as network quality, service experience, security, and trust is missing, viewing them as part of an interconnected process. To address this gap, this study proposes an integrated model that conceptualizes the adoption of cloud-based learning as a process built on infrastructure. Specifically, the model suggests that network quality influences service experience, which, together with security, contributes to building trust, while trust directly influences intention to use. Through this approach, the study provides a more complete and structured understanding of the factors that influence the adoption of cloud systems in higher education.

3. Conceptual Model and Hypothesis

Traditional e-learning systems are different from cloud systems because they are within institutional systems, and their performance is determined by the internal design and functionality of these systems. While cloud-based learning services rely on external infrastructure, including distributed servers, remote data storage environments, and network connectivity. According to Sultan (2010), students' experiences with cloud-based learning platforms are shaped by the design of the system interface, the reliability, and the stability of the infrastructure that enables access to these services. In their study, Al-Fraihat, Joy, Masa'deh, and Sinclair (2020) found four constructs as determinants of e-learning use, which were quality of the educational system, quality of the support system, quality of the learner, and perceived usefulness. According to the literature, trust-related factors also play an important role in the use of digital learning systems. User behaviors in online environments are greatly influenced by their trust in system reliability, data protection, and institutional integrity (Anwar, 2021). According to Wu and Plakhtii (2021), cloud computing learning has many advantages because it improves the organizational and educational process of the institution, increases the academic performance of students, and enables data security and reliability. Since data storage and processing occur on remote servers that are often managed by external service providers, users must rely on the provider's ability to ensure data protection, privacy, and system integrity. Studies highlight perceived security as a key factor influencing the formation of trust in cloud computing environments (Al-Shqeerat, Al-Shrouf, Hassan, & Fajraoui, 2017).

Infrastructure reliability is a crucial factor that shapes user experiences in cloud-based learning ecosystems. When the network connection is unstable or slow, students may blame their performance problems on the learning platform itself, even if the underlying system is functioning properly. Despite studies being conducted in this area, there is a notable lack of inclusion of infrastructure support as one of the key factors. Drawing on these theoretical

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perspectives and those discussed in the first part of the paper, our study conceptualizes cloud-based learning adoption as a layered process in which infrastructure conditions shape the service experience, which in turn influences the formation of student trust and behavioral intention. Therefore, the framework proposed in Figure 1 follows a sequential path.

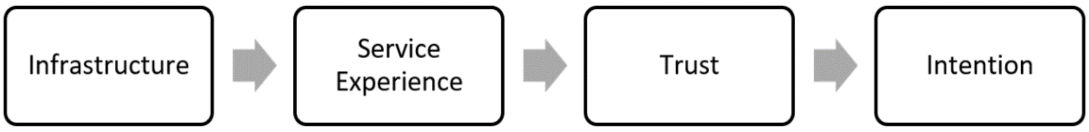

Figure 1. Proposed framework flow.

In this paper, network technology is a fundamental infrastructural element that shapes the overall students' experience with its cloud learning systems.

3.1. Hypotheses Development

Based on the literature, our study tests four hypotheses. In cloud-based platforms, unstable or slow connections negatively affect students' perceptions of the usability and performance of the system. Consequently, the reliability and quality of the network connection are expected to play a critical role in shaping students' overall evaluation of cloud-based learning services (Almaiah, Al-Khasawneh, & Althunibat, 2020; Sultan, 2010). Based on this evidence, the first hypothesis of this study is:

H_1: Network quality positively affects service experience.

Students' positive experiences with system functionality and performance contribute to perceptions of reliability and usability because when cloud-based learning services operate smoothly and efficiently, students are more likely to perceive the platform as trustworthy. Consequently, they will use it more and support their academic activities on these platforms. Trust, as one of the key factors in the use of cloud computing in education, has been seen in many scientific studies (Anwar, 2021; Singh & Thurman, 2019; Sun, Tsai, Finger, Chen, & Yeh, 2008). For these reasons, our second hypothesis assesses the relationship between service experience and user trust.

H_2: Service experience positively influences trust.

Meanwhile, other studies note that perceived security is an important precursor to trust in digital services and cloud computing environments (Anwar, 2021). Based on these findings, the third hypothesis can be formulated as follows:

H_3: Security positively affects trust.

Since students who trust the reliability and integrity of the system are more likely to rely on it for academic activities, they intend to continue using it in the future. Trust is seen as a key determinant of user behavioral intention in technology-mediated environments (Gefen, Karahanna, & Straub, 2003; Ratten, 2015). We formulated the fourth hypothesis as follows:

H_4: Trust positively influences students' intention to use cloud-based learning services.

The conceptual relationships between the four constructs are illustrated in Figure 2.

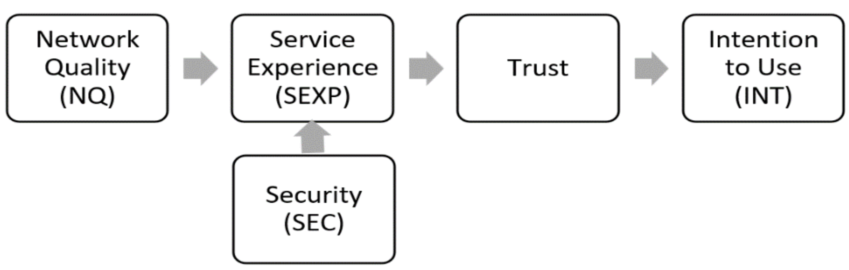

Figure 2. Conceptual model of infrastructure-driven trust-based adoption of cloud-based learning services in higher education.

Our conceptual model positions network quality as a key driver of service experience, along with perceived security. Service experience, along with perceived safety, contributes to the formation of trust. Then, trust acts as the main mechanism through which technological conditions translate into students' intention to use cloud computing-based learning services.

4. Methodology

For this study, the data used were collected through surveys among first-cycle students at the Faculty of Technical and Natural Sciences at the University of Vlora in Albania during January 2026. The selected participants were studying computer science, information technology, or informatics. They had previous experience with various cloud-based learning platforms, including tools such as Google Drive, SaaS, OneDrive, an institutional information management system, and cloud-based learning systems. Data collection was done through a structured online questionnaire that was sent electronically to the students. Their participation was voluntary, and they were informed about the purpose of the study and assured that their data would be confidential. After checking for completeness and consistency, 178 valid responses were retained for further analysis. There were no major issues with the data related to the constructs of the model, and all answers were suitable for statistical analysis.

Since students often use cloud services for their studies, teamwork, and data management, this group provides a relevant setting to study how infrastructure influences the adoption of cloud-based tools. Table 1 presents a more detailed summary of students' cloud usage habits.

From the descriptive analysis, it is noted that a large number of students use cloud services regularly. About 79.2% mainly used tools like SaaS, while 71.9% depended on Wi-Fi connections. The high rate of SaaS and wireless

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access usage demonstrates the importance of including network quality and security as two of the key elements in the conceptual model we have proposed.

Table 1. Background information on student cloud usage.

Item	Category	Percentage (%)
Frequency of cloud use	Often	34.3
	Sometimes	25.8
	Very often	23.6
	Rarely	16.3
Cloud service used	SaaS (Google Drive, OneDrive, Gmail, etc.)	79.2
	Both (SaaS and IaaS/PaaS)	18.5
	IaaS / PaaS	2.2
Network type used	Wi-Fi	71.9
	4G/5G	20.2
	LAN	7.9

The questionnaire was developed based on previous literature on e-learning, cloud-based learning, information systems success, and research on digital trust (Al-Fraihat, Joy, Masa'deh, & Sinclair, 2020; Alenezi, 2023; Anwar, 2021; Carabregu-Vokshi, Ogruk-Maz, Yildirim, Dedaj, & Zeqiri, 2024; Gefen, Karahanna, & Straub, 2003; Sayginer, 2023; Sun et al., 2008; Wu & Plakhtii, 2021). All constructs were modeled as reflective and measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Our proposed model includes five latent variables: Network Quality (NQ), Service Experience (SEXP), Security (SEC), Trust (TRUST), and Intent to Use (INT). The proposed research model was evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM), a method widely applied in prediction-oriented research, theory development, and studies involving multiple latent constructs and mediation relationships. Compared with covariance-based SEM approaches, PLS-SEM focuses on maximizing the explained variance of endogenous constructs rather than reproducing covariance matrices, making it particularly suitable for exploratory and prediction-focused studies (Rigdon, Sarstedt, & Ringle, 2017; Sarstedt, Ringle, & Hair, 2021). Partial Least Squares Structural Equation Modeling (PLS-SEM) includes measurement model estimation and structural model estimation. In the first stage of analysis, the measurement model was evaluated to assess the reliability and validity of the reflective constructs. Indicator reliability was examined through outer loadings, while internal consistency reliability was assessed using Cronbach's alpha and Composite Reliability (CR). Convergent validity was evaluated using the Average Variance Extracted (AVE), and discriminant validity was assessed using the Heterotrait–Monotrait ratio (HTMT).

During the measurement validation phase, the assessment of discriminant validity showed a significant overlap between cloud service quality and perceived performance. For this reason, instead of treating these as separate but statistically similar constructs, they were merged into a single construct called Service Experience (SEXP). This approach also aligns with how students generally evaluate cloud-based systems as a whole. They usually form a single general judgment based on their experience rather than distinguishing between technical qualities and performance results. This new construct represents students' overall assessment of the functionality and performance of cloud-based learning services as a single factor. Also, this change increases the validity of the measurement while remaining consistent with the theoretical framework that is more focused on infrastructure.

In the next stage, the structural model is tested by estimating path coefficients (β), coefficients of determination (R^2), and effect sizes (f^2). The significance of the proposed relationships was determined using bootstrapping with 5,000 resamples, which provided reliable standard errors and confidence intervals. According to the literature, this nonparametric resampling method supports accurate conclusions about the importance of relationships in the structural model (Rigdon, Sarstedt, & Ringle, 2017; Sarstedt, Ringle, & Hair, 2021). Effect sizes (f^2) were calculated by comparing the R^2 values from the full model with those from models where specific paths were removed. This process helps determine the practical importance of each predictor variable, beyond just statistical significance.

Data analysis was performed using the R programming language. The seminr package was used, which is often used for estimating PLS-SEM models and performing bootstrapping procedures.

5. Results

5.1. Measurement Model

First, the reflective measurement model was evaluated. This evaluation focused on three main areas: internal consistency, reliability, convergent validity, and finally, discriminant validity (Rigdon, Sarstedt, & Ringle, 2017; Sarstedt, Ringle, & Hair, 2021). Internal consistency reliability was assessed through Cronbach's alpha and Composite Reliability (CR). Meanwhile, the assessment of convergent validity included the calculation of the Average Variance Extracted (AVE). To assess discriminant validity, we used the Heterotrait-Monotrait (HTMT) ratio.

In accordance with the defined PLS-SEM guidelines, according to Sarstedt, Ringle, & Hair (2021), CR values above 0.70 and AVE values above 0.50 indicate satisfactory reliability and convergent validity. As shown in Table 2, all constructs exceed the recommended composite reliability threshold (CR > 0.70) and demonstrate AVE values above 0.50, confirming sufficient convergent validity. Although Cronbach's alpha for Network Quality ($\alpha = 0.495$) is below the conventional reference point of 0.70, its composite reliability (CR = 0.736) exceeds the acceptable level. Composite reliability is considered more appropriate for PLS-SEM because it matches well with external loadings (Sarstedt, Ringle, & Hair, 2021), so the construct was retained. Furthermore, indicator loadings were generally above 0.70, with a Network Quality indicator retained based on theoretical significance and acceptable overall reliability.

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Table 2. Reliability and convergent validity.

Construct	Cronbach's α	Composite Reliability (CR)	AVE
NQ	0.495	0.736	0.512
SEXP	0.895	0.921	0.661
SEC	0.913	0.946	0.853
TRUST	0.877	0.924	0.803
INT	0.924	0.953	0.870

HTMT is a reliable method for assessing the distinctness of constructs in variance-based structural equation modeling (SEM) (Sarstedt, Ringle, & Hair, 2021). The results show that most HTMT values are below the commonly recommended threshold of 0.90 (Table 3). However, two values slightly exceed this threshold, reaching 0.912 and 0.957. According to the more lenient criteria suggested in the literature, HTMT values below 0.95 can still be considered acceptable, especially in exploratory research contexts (Hair, Matthews, Matthews, & Sarstedt, 2017). Therefore, discriminant validity is considered acceptable for the constructs included in this study. Bootstrapped confidence intervals for the HTMT ratios did not indicate any critical issues that would compromise discriminant validity.

Table 3. Discriminant validity (HTMT Ratios).

Construct	NQ	SEXP	SEC	TRUST	INT
NQ	—	0.957	0.522	0.568	0.655
SEXP		—	0.657	0.703	0.761
SEC			—	0.877	0.765
TRUST				—	0.912
INT					—

In conclusion, overall, the measurement model demonstrates satisfactory reliability and validity and supports the assessment of structural relationships. Also, none of the bootstrapped HTMT confidence intervals included the value 1.00, indicating acceptable discriminant validity.

5.2. Structural Model

After the model confirmation of the measurement model, the structural model is estimated to analyze the relationships between latent variables and to test the proposed hypotheses. Path coefficients (β) were used to measure the direction and strength of the relationships between constructs. Meanwhile, the coefficient of determination (R^2) assessed the level of explained variance in endogenous variables. To determine the individual contribution of each construct in the model, the effect size (f^2) was used, while the statistical significance of the relationships was tested using the bootstrapping technique with 5,000 resamples. Confidence intervals were used to confirm or reject the four study hypotheses (Sarstedt, Ringle, & Hair, 2021).

All hypothesized relationships show statistically significant results, and the bootstrapped confidence intervals exclude zero, confirming support for all hypotheses, from H1 to H4. Network Quality exerts a strong positive effect on Service Experience ($\beta = 0.720$, $t = 19.802$, 95% CI [0.646, 0.788], $p < 0.001$).

Service Experience positively influences Trust ($\beta = 0.232$, $t = 3.436$, 95% CI [0.102, 0.367], $p < 0.01$). Security demonstrates a strong positive effect on Trust ($\beta = 0.657$, $t = 12.103$, 95% CI [0.541, 0.757], $p < 0.001$). Trust strongly influences Intention to Use ($\beta = 0.821$, $t = 26.408$, 95% CI [0.756, 0.879], $p < 0.001$). The results of the structural model are represented in Table 4.

Table 4. Structural model results.

Hypothesis	Path	β	t-value	95% CI	Result
H1	NQ → SEXP	0.720	19.802	[0.646, 0.788]	Supported
H2	SEXP → TRUST	0.232	3.436	[0.102, 0.367]	Supported
H3	SEC → TRUST	0.657	12.103	[0.541, 0.757]	Supported
H4	TRUST → INT	0.821	26.408	[0.756, 0.879]	Supported

The coefficient of determination (R^2) was used to assess the explanatory power of the structural model. In numerous studies using the PLS-SEM method, R^2 values around 0.25, 0.50, and 0.75 are commonly interpreted as weak, medium, and high levels of explanatory power, contingent upon the context of the study. The results show that the model explains 51.9% of the variance in service experience, also, the model explains 66.6% of the variance in trust, and 67.4% of the variance in intention to use. These values indicate that the model has medium to high explanatory power, especially with regard to trust and intention of use.

Overall, high R^2 values suggest that the model captures a substantial portion of the variance in the key endogenous constructs, indicating that the proposed framework, based on infrastructure and trust, gives a robust explanation for the adoption of cloud-based learning in the study context.

Effect sizes (f^2) were calculated by comparing the R^2 of the full model with those of the reduced models excluding individual predictors (Table 5).

Table 5. Effect Sizes (f^2) analysis.

Path	Target	R^2 Included	R^2 Excluded	f^2	Interpretation
NQ → SEXP	SEXP	0.519	0.000	1.078	Large
SEXP → TRUST	TRUST	0.666	0.634	0.097	Small
SEC → TRUST	TRUST	0.666	0.388	0.833	Large
TRUST → INT	INT	0.674	0.000	2.065	Very Large

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It turns out that network quality has a significant practical impact on the service experience, underscoring the importance of stable connectivity in students' evaluation of cloud-based learning services. Security also shows a strong effect on trust, suggesting that perceptions of data protection and system reliability are essential for establishing trust in cloud platforms. On the other hand, trust exerts a very strong influence on intention to use, underlining its key role in the structural model.

Overall, the results of the structural model provide empirical support for the proposed infrastructure- and trust-based framework. The relatively high R^2 values for trust and intention to use indicate that the model explains a substantial portion of the variance in students' intentions for adoption. This suggests that the model provides a consistent explanation for the adoption of cloud-based learning in the study context. Figure 3 presents the structural model with the standardized path coefficients and R^2 values for the endogenous constructs.

Figure 3. Structural model (Standardized path coefficients and R^2 values).

6. Discussions

In this study, the purpose is to analyze the factors influencing the adoption of cloud-based learning in higher education. The results of the paper show that network quality plays a significant role in the service experience ($\beta = 0.720$; $f^2 = 1.078$). This indicates that students' experiences of cloud-based learning environments are mainly influenced by how stable and reliable the internet connection is. In traditional models such as UTAUT and TAM, it is usually looked at how users think and feel about the technology, i.e., how useful the technology is or how easy it is to use (Noh & Amron, 2021; Sayginer, 2023). Unlike these models, our study shows that the quality of the infrastructure is crucial in determining the user experience. This means that network reliability is a key factor that influences how students perceive and evaluate the entire learning system.

The other two factors, security and service experience, turn out to be important factors in building trust, indicating that students value not only functionality but also the security of platforms. Perceived security was the strongest factor influencing trust ($\beta = 0.657$; $f^2 = 0.833$), indicating that data privacy, reliability, and system protection are very important in cloud-based learning environments. Meanwhile, service experience also influences trust creation but at lower levels than security ($\beta = 0.232$; $f^2 = 0.097$). Its lower impact suggests that students see a difference between systems that work well and those they believe are secure. Because trust in a given system is not only about its performance, but is also strongly linked to how secure users feel the system is. This is consistent with previous studies that highlight the key role of privacy and security in building trust in digital environments (Anwar, 2021).

While trust has a strong effect on students' intention to use the system ($\beta = 0.821$; $f^2 = 2.065$), confirming its role as the main link between how students evaluate the infrastructure and experience and their willingness to use the system. It should be noted that our model does not show a direct relationship between network quality or service experience and intention; it suggests that adoption occurs primarily through building trust from antecedent factors.

Our research is enhanced by integrating infrastructure, experience, and security factors into a single trust-based model. The findings extend existing knowledge about cloud systems used in e-learning and how adoption of this technology occurs. Past studies have focused primarily on the importance of information quality, system quality, and service quality in shaping user satisfaction and system usage (Al-Fraihat, Joy, Masa'deh, & Sinclair, 2020) as well as the role of thinking and perception in adaptation (Chanda, Vafaei-Zadeh, Hanifah, & Ramayah, 2024). These studies have paid less attention to infrastructure quality. This study places network quality at the heart of the adaptation process, enriching existing theories and providing a more complete understanding of how users behave in cloud-based learning environments. The effectiveness of digital learning environments depends not only on how well the teaching is designed or how functional or interactive the platform is, but also on how robust the infrastructure is. This result is consistent with broader perspectives on digital transformation in higher education, which emphasize the need for more advanced technological and organizational strategies (Alenezi, 2023). This study also suggests that the benefits of digital learning environments depend on the reliable and secure conditions of the system. And these benefits are numerous; many studies have shown that digital learning environments can increase learning outcomes, student engagement, and collaboration between students (Ahmed et al., 2025; Carabregu-Vokshi, Ogruk-Maz, Yildirim, Dedaj, & Zeqiri, 2024).

This research offers several important practical conclusions. Higher education institutions using the cloud for education should view network reliability as a strategic priority, not just a technical necessity. Investing in infrastructure, stable internet access, system monitoring, and fast technical support can greatly improve the service experience. Also, since perceived security strongly influences trust, institutions should take visible steps to protect student privacy, maintain consistent cybersecurity practices, and clearly communicate data management policies. Cloud systems in education must be viewed as a comprehensive approach, starting from the infrastructure that is the basis of the experience with the system. Failure to improve the features of the system as a whole can limit the long-term success of digital learning programs.

Overall, this research provides a comprehensive, infrastructure-focused view of cloud-based learning adoption. Unlike past studies that examine quality, performance, or trust individually, this study brings together infrastructure conditions, user experiences, and trust building into a single integrated framework. It provides a

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more realistic and theoretical understanding of how students interact with cloud-based learning environments in higher education by viewing adoption as a layered process driven by trust. However, the study also has limitations, such as the focus on a specific context and the use of self-reported data. Future studies could expand the model by including other factors influencing cloud computing in education or by analyzing different educational contexts.

7. Conclusions

This study built a single structural model to analyze how cloud-based learning is implemented in higher education, using a framework that integrates both infrastructure and trust. The study goes beyond traditional approaches that focus solely on individual perceptions; it assesses factors such as network quality, security, service experience, and trust.

The research results showed that network quality is a key factor and directly affects students' experience with cloud services. This means that the stability of the infrastructure of these systems is crucial in how students evaluate cloud-based learning systems. Also, data protection and system integrity are very important in digital learning, and security is identified as the main factor influencing trust building. Experience and perceptions of the infrastructure with the intention of use are related to the trust factor.

From a theoretical perspective, the study outlines the adoption of cloud learning as a multi-level process, where the reliability of the infrastructure influences the experience, and these, together with security, lead to the building of trust. This study extends existing models of technology adoption and provides a more complete understanding of the use of digital learning by including infrastructure factors at the core of the model. From a practical perspective, the results of this work suggest that universities should focus on improving network quality and strengthening security mechanisms. The institution should seriously consider investments in infrastructure, monitoring systems, take cybersecurity measures, and implement transparent data policies in order to increase student trust. A good combination of technical infrastructure and trust-building is crucial for the long-term adoption of cloud-based learning.

This study also has limitations that will be taken into account in future studies. The data were collected only from one university, which may limit the generalizability of the results to other contexts. Also, the study does not capture changes over time because its design is cross-sectional. We focused on student perceptions and did not include objective data on academic performance or actual use of the systems. In other studies, the model should be tested in different national and institutional contexts. To understand changes in trust and adoption over time, it is important to use a longitudinal design. However, integrating objective data on student participation and academic performance may provide a more complete picture of the impact of these factors. Also, other studies could examine additional factors such as institutional support, digital skills, and previous experience with cloud technologies, or user contentment.

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