Journal of Applied Engineering and Technological Science
Vol 7(2) 2026: 1045-1063

EXPLORING CLOUD-BASED E-LEARNING ADOPTION IN DEVELOPING NATIONS: A COMPREHENSIVE REVIEW

Khalilullah Khalid[1], Rajashree Jain[2]*
Symbiosis Centre for Research and Innovation, Symbiosis International Deemed University, Pune, India[1]
Symbiosis Institute of Computer Studies and Research, Symbiosis International Deemed University, Pune, India[2]
rajashreejain@gmail.com

Received: 11 October 2025, Revised: 09 April 2026, Accepted: 12 April 2026
**Corresponding Author*

ABSTRACT
Digital transformation in the form of Cloud-based e-learning (CBEL) in higher education has enabled anytime, anywhere learning environments. The literature on the adoption models for CBEL from developing nation's perspectives is scarce. A current study presents a systematic literature review of CBEL adoption in developing nations. The PRISMA framework was used for the study. It articulates 27 different articles published during 2019-2025. The articles were chosen from Scopus and WoS databases. The review presents user intention to adopt to CBEL as high, but actual adoption depends on a number of contextual factors such as infrastructure, connectivity, training, support, security and policy. The review further reveals a strong reliance on user-level models such as TAM and UTAUT, with limited integration of organizational perspectives and reliance on perceptual measures over actual outcomes. Consequently, this study proposes an integrated framework combining technological readiness, organizational support, user acceptance, and adoption outcomes. Theoretically, CBEL adoption in developing countries cannot be explained only through user acceptance factors but also by organizational and infrastructural conditions. From a practical perspective, HEIs administrators and policymakers should view CBEL as a sociotechnical system, not only a digital tool. Future research should focus on longitudinal empirical validation of the proposed framework.
***Keywords**: Cloud-based e-learning, technology adoption frameworks, educational technology, higher education, developing countries*

1. Introduction

The rapid development of information and communication technologies has fundamentally changed the delivery of higher education, and e-learning has become an essential part of this transformation. Khan (2005) defines e-learning as an innovative model of learning that combines the benefits of several educational technologies with many forms of content suitable for a flexible, massive, open, and distributed environment for learning that supports a sound designed, student-centric, interactive, collaborative, and facilitated environment to learn for anyone, anywhere, and at any time. The growth of e-learning has revolutionized traditional education by empowering flexible, learner-centered access to education with no time and place limitations (Thongsri et al., 2019). The COVID-19 pandemic and its resulting lockdown have also made e-learning increasingly significant, particularly in higher education (HE) worldwide. E-learning is now a necessity for higher education institutions (HEIs), particularly after COVID-19, as it has received considerable attention including developing nations (Bhardwaj et al., 2021). Therefore, no HEI can afford to ignore e-learning and related technologies.

With the rising demand for cost-effective and scalable educational solutions, cloud computing (CC) is an influential enabler of improving the delivery, accessibility, and management of e-learning systems (Eljak et al., 2024). E-learning platforms based on cloud technologies, often referred to as cloud-based e-learning (CBEL) offers dynamic resource allocation, real-time collaboration, and improved scalability, especially beneficial for HEIs in developing nations with infrastructural limitations (Elmasry & Ibrahim, 2021). The need for adopting such technology became even more apparent during the COVID-19 pandemic, which forced HEIs across the globe to quickly adopt e-learning, which highlighted the necessity for a robust, cloud supported e-learning platforms (Al-Hajri et al., 2021; Pokhrel & Chhetri, 2021).

Providing and establishing e-learning systems and infrastructure with traditional tools presents numerous challenges regarding scalability, accessibility, ease of use and usability, security, management, cost, and more (Eljak et al., 2024). Although the educational benefits of cloud-hosted systems are widely recognized, adoption remains uneven across countries and institutions. In contrast to developed regions, HEIs in developing countries often face limitations such as inadequate infrastructure, inconsistent connectivity, limited institutional funding, lower digital readiness, and low policy support, which affect the adoption and sustainability of digital transformation (Wang et al., 2026). These differences are not only technical; but also how institutions organize technology, support users, and integrate technology into pedagogy. As a result, CBEL in HEIs in developing countries must be understood as a sociotechnical and institutional process rather than only as a matter of user willingness to adopt technology (Lopes et al., 2022; Wang et al., 2026).

From the adoption perspective, research confirms that the factors of CBEL adoption vary across contexts. As an example in Oman, students' intention to use CC systems in HE during the COVID-19 period was significantly influenced by perceived ease of use (PEoU), perceived usefulness (PU), perceived reliability, and responsiveness (Al-Hajri et al., 2021). In Ghanaian technical universities, faculty adoption was shaped by pedagogical innovation, e-infrastructure readiness, security, provider support, and institutional location, with infrastructure-related issues remaining central (Armah & Ali, 2024). In Jordan, a more recent unified model integrating UTAUT constructs showed that behavioral control, effort expectancy, and social influence significantly influenced academics' attitudes toward adopting sustainable collaborative cloud-based systems in higher education (Feng et al., 2025). These findings indicate that while user related acceptance factors remain important, organizational readiness, infrastructural capacity, and broader environmental support must also be considered when assessing the adoption of CBEL in HEIs in developing countries.

Theoretical and methodological fragmentation in the existing literature remains another issue. Many studies explain adoption through established acceptance models such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology-Organization-Environment (TOE) framework, and the Diffusion of Innovation (DOI) theory. These theoretical models provide important foundations for understanding technology adoption, however, these models are not used consistently, and they do not always capture the same dimensions of CBEL adoption. TAM and UTAUT are frequently used to explain PU, PEoU, and behavioral intention (BI). While TOE and DOI as organizational and environmental models are less consistently applied, they may be more suitable for developing contexts where infrastructure, management support, regulation, and provider conditions matter strongly (Bhardwaj et al., 2021; Hussein & Hilmi, 2020; Njenga et al., 2019). In another work the successful cloud-hosted virtual learning environments depend not only on acceptance but also on legal, operational, educational, quality, and cultural requirements, which suggests that cloud-based educational systems require broader and more context sensitive assessment approaches (Malkawi et al., 2024). Furthermore, there is a lack of integrated synthesis that examines adoption drivers, barriers, theoretical models, and impact outcomes in developing nation contexts simultaneously (Bhardwaj et al., 2021). As a result, it remains unclear how these dimensions interact to influence the actual implementation and effectiveness of CBEL in higher education, particularly in low-resource environments (Wang et al., 2026).

To address the above research problems and background, the following research questions are defined:

1. To what extent cloud-based e-learning is adopted in HEIs in developing countries?
2. What key drivers and barriers impact CBEL adoption, especially in developing nations?
3. How to measure and assess cloud-based e-learning adoption in HEIs?

To address above questions and research problem, this study aims to systematically review empirical research on CBEL adoption in HEIs in developing nations. The objectives of this study are to examine the state of CBEL adoption in developing countries, to identify the major adoption drivers and barriers, to analyze the popular models and methods used for adoption assessment, to review the impact measures employed in the literature, and to propose an integrated framework suitable for HEIs in developing countries.

The study contributes to the literature in three ways. By providing a focused synthesis of empirical research on how CBEL adoption in the context of HEIs in developing countries and how its adoption is assessed, rather than as a single solution. Moreover, by critically comparing individual and user-level adoption models with organizational and contextual factors, this study clarifies the need for integrated approaches in developing contexts. In addition, the proposed framework, anchored in reviewed studies, builds a suitable foundation for future empirical assessment in low-resource and institutionally diverse HEIs in developing nations.

2. Research Methods

Systematic literature review (SLR) approach was adopted to synthesize empirical evidence on CBEL adoption in developing countries. The established guidelines, Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) were followed to systematically synthesize selected research. This method and guidelines ensure transparency, reproducibility, and methodological rigor (Page et al., 2021). The review process is structured based on defined stages, including search strategy, study selection and exclusion criteria, data extraction, and analysis given in PRISMA guidelines, as follows.

2.1. Data Sources and Search Strategy

Scopus and Web of Science two major academic sources of high-quality journal articles, were selected for searching empirical studies used in the main review.

On the search and related perspectives, multiple keyword combinations were employed to ensure comprehensive coverage, due to the variation in terminology in information technology and educational technology. "e-learning" and "cloud computing," supplemented with context-specific terms such as "higher education" and "universities", were the main search keywords used in the search process. The string used in search was:

("cloud-based e-learning" OR "cloud computing in education" OR "cloud learning") OR (cloud AND computing OR cloud AND based AND "e-Learning" OR "eLearning" OR "e learning" OR "Online Learning" OR "Online Education" OR "Distance Learning" OR "Distance Education")
AND ("adoption" OR "acceptance" OR "usage")
AND ("higher education" OR universities)
AND ("developing countries" OR "emerging economies")

2.2 Inclusion and Exclusion Criteria

The inclusion and exclusion criteria, as the main aspect of an SLR, were considered based on PRISMA guidelines, and the following were applied:

Inclusion criteria:
- Include studies published between 2019–2025
- Empirical studies (quantitative, qualitative, or mixed methods)
- Focus on studies that discuss the adoption of e-learning with cloud-based solution
- Conducted in developing countries
- Published in peer-reviewed sources

Exclusion criteria:
- Studies focusing only on traditional e-learning
- Conceptual or non-empirical studies
- Studies not related to higher education
- Articles without full-text access

Furthermore, since e-learning is a multidisciplinary concept or a sociotechnical subject (Lopes et al., 2022) that can be used in any field in HE or any other type of education, therefore, research pertaining to "e-Learning based on cloud" is mainly studied by the fields of computer science and education. Scopus statistics presented in Figure 1 illustrate that selected studies are mainly published under education and education technology, computer science, engineering, and some other themes. However, the development of e-learning is primarily related to computer science and technology, but its applications exist in almost all fields, therefore, papers from other backgrounds were also included, e.g., the study of CBEL in healthcare, social sciences, and management.

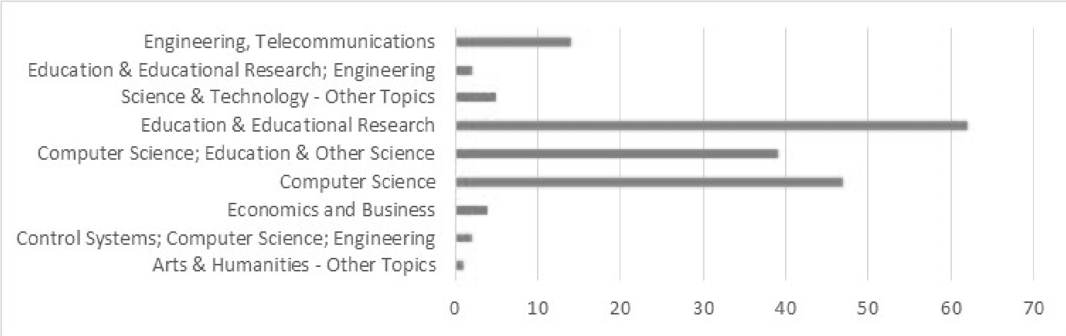

Fig. 1. Research areas of the selected studies

2.3 Study Selection Process

The initial search resulted in 138 studies. After removing duplicates and irrelevant records based on inclusion and exclusion criteria, 42 studies remained as shown in Figure 2. Following abstract screening and full-text assessment, 27 empirical studies were selected for final analysis, and summarized and categorized by country in Table 1. Some fundamental studies were also included for a detailed review from Emerald, ProQuest, and Google Scholar. Figure 2 illustrates the PRISMA flow diagram and shows the identification, screening, eligibility, and inclusion process.

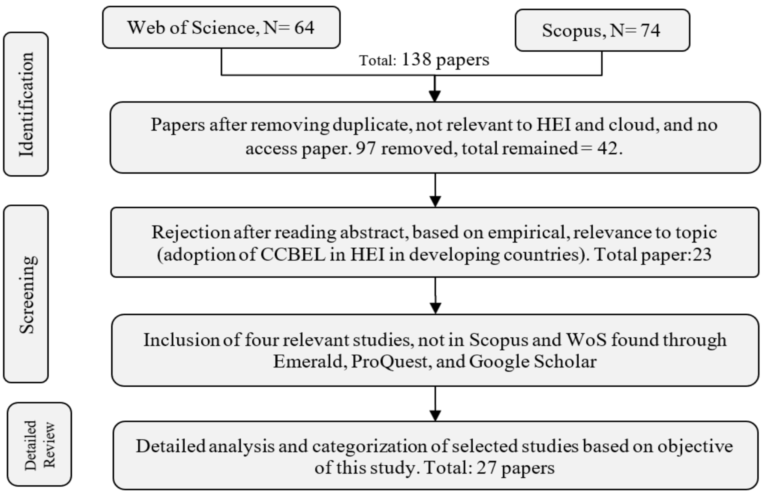

Fig. 2. Selection, exclusion, and the inclusion process of the review

2.4 Data Extraction and Analysis

Using structured data extraction process, the context (country, institution type) of selected studies, research methodology, adoption models (e.g., TAM, TOE, UTAUT, DOI), key drivers and barriers, and reported outcomes were extracted.

The identification of frequent patterns and categorization into key themes using a qualitative thematic synthesis approach was conducted. Four main themes were extracted and categorized including adoption drivers, adoption barriers, assessment method and theoretical models, measuring factors, and finally proposing an integrated CBEL assessment framework, each presented in Results subsections.

2.5 Development of Conceptual Framework

The proposed framework was developed inductively based on recurring themes identified across the reviewed studies and supported by established theoretical models including TAM, UTAUT, TOE, and other related adoption frameworks. The framework in Figure 7 integrates both individual-level (user acceptance) and organizational-level (institutional readiness) factors to reflect the realities of developing country contexts. This approach ensures that the framework is both empirically grounded and theoretically informed.

3. Results and Discussion

e-Learning and cloud computing (CC) are innovative technologies and their combination has already brought about a paradigm shift in information technology (IT) and education. Integrating e-learning with CC or designing cloud-based e-learning (CBEL) brings an extra benefit to the HEIs, such as improving the quality of learning by reducing the overhead of IT resources management and letting higher education institutions (HEIs) focus on teaching and learning (Hussein & Hilmi, 2020). Although CBEL is effectively used in developed countries, its adoption in developing nations remains relatively low (Aini et al., 2020). To address this issue here the results of the systematic review is presented in line with the thematic synthesis described in the methodology. Theses 27 empirical studies selected through the PRISMA screening process and summarized in Table 1, make basis for result of analysis in this section.

Table 1 - Summary of included studies: context, model, adoption factors, and key findings

Adoption Level	Model Used	Key Drivers	Key Barriers	Impact	References
Countries with higher adoption reported: Thailand, Kenya, India, Bangladesh, Iraq, Sri Lanka, Somalia	UTAUT+ extension, TAM + extensions, TOE, IS Success factors, DeLone & McLean models	PU, PE, SI, Tech. readiness, PEOU, institutional support, low cost, Sustainability, fault tolerance, scalability, flexibility, open-source control, intelligent assistance	Security/privacy issues, ICT skills gaps, limited infrastructure, resistance to change, CSP-Lock (vendor-lock)	Higher adoption of more than 80%, active SaaS usage, cloud-based LMS applied, post-COVID adoption increased, improved collaboration and engagement, and learning continuity in all cases.	(Thongsri et al., 2019) (Njenga et al., 2019) (Bhardwaj et al., 2021)(Maisha & Shetu, 2023) (Assalaarachchi et al., 2023) (Shakor & Surameery, 2021) (Farah Ali et al., 2024)
Moderate adoption: Malaysia, Saudi Arabia, Lebanon, India, Indonesia, Pakistan, Ghana	TAM, UTAUT, TOE, extended with need and innovativeness, intrinsic/ extrinsic motivation, as a moderator, the IS continuance model, the IS discontinuance model, DOI, some studies with a custom model	PU, EoU, Need, organizational support, motivation, low cost, cultural exposure, virtual classrooms, eco-friendly, backup/recovery, on-demand content, USat	Policy gaps, insufficient infrastructures, low awareness, integration issues, cost & complexity, resistance to change, vendor-lock,	Moderate use reported, Moderate BI and platform usage, about 30 to 79%, improved engagement and collaboration in some studies. SaaS tools (e.g., Google Classroom) facilitate a paperless environment and simplify assessment. promotes secure documentation and access to learning materials, enhanced LX, and UX.	(J. A. Kumar et al., 2020) (Hussein & Hilmi, 2020) (Qasem et al., 2020) (Alajlan et al., 2020) (Kayali & Alaaraj, 2020) (Gupta et al., 2022) (R. Kumar, 2023) (Sharma et al., 2025) (Sugandini et al., 2022) (Shahzad et al., 2020) (Armah & Ali, 2024)
Comparatively low / emerging adoption reported: Libya, Nigeria, Iraq, Turkey, Iran, Afghanistan	TOE, extended with impact context, hybrid framework, TTF	Interest in ICT use, cost-effectiveness, PEOU, SQ, research support, improvement in education,	Weak infrastructure, funding and training gaps, low cloud awareness, Lack of expertise, limited bandwidth, vendor-lock	Emerging or pilot-stage adoption, mostly conceptual or pre-implementation assessment, reported	(Al Ghawail et al., 2019) (Eze et al., 2020) (Matthew et al., 2021) (Hashim et al., 2022) (Muhisn et al., 2023) (Aydin, 2021) (Abdekhoda et al., 2022) (Barikzai et al., 2025) (Rehaimi et al., 2024) A general study

Note: perceived usefulness (PU), perceived ease of use (PEOU), relative advantage (RA), performance expectancy (PE) social influence (SI), competitive pressure (CP), user satisfaction (USat), competitive advantage (CA), compatibility, (compt), system quality (SQ), information quality (IQ), service quality (SRQ), task-technology fit (TTF), learning experiences (LX), user experience (UX), learning management system (LMS).

In addition to showing list of studies, Table 1 also provides a consolidated overview of the selected studies, including adoption levels, models used, key drivers, barriers, and reported impacts across different countries. The table forms the empirical basis for identifying patterns and variations discussed in the following subsections, which are presented based on the thematic categories identified during the analysis process and focus on the adoption of CBEL in HEIs in developing countries.

3.1 CBEL Adoption Drivers and Enabling Conditions

The integration of e-learning with the cloud computing model provides several advantages, including accessibility, flexibility, cost efficiency, and scalability, which make it attractive for HEIs. CBEL enables HEIs to offer scalable, on-demand self-service learning resources that is available anytime, from anywhere, and using any device, supporting continuity of education even during major lockdowns like the COVID-19 (Aydin, 2021; Bhardwaj et al., 2021).

Across the selected studies, CBEL adoption is consistently framed as a sociotechnical process rather than only a technical deployment. This is aligned with treating CBEL adoption in higher education as a multidisciplinary and sociotechnical phenomenon (Lopes et al., 2022). Within this framing, three clusters of drivers recur across contexts: perceived benefits at the user-level, institutional enabling conditions, and the economic or operational value proposition of cloud-based service models.

At user-level, studies using TAM and its extensions repeatedly report PU as the strongest driver of acceptance (Alajlan et al., 2020; Hussein & Hilmi, 2020; Maisha & Shetu, 2023). Studies conducted in Malaysia, Saudi Arabia, and Bangladesh demonstrate that when users perceive tangible improvements in learning performance, their intention to adopt significantly increases (Alajlan et al., 2020; Hussein & Hilmi, 2020; Maisha & Shetu, 2023). In these studies, PU is typically interpreted as improvement in learning performance, suitability, and productivity. Second, PEoU is commonly significant, and its influence is often depending on conditions (e.g., connectivity, digital skills, technical support), particularly in low-resource environments such as Nigeria, Afghanistan, and Iraq (Barikzai et al., 2025; Eze et al., 2020; Hashim et al., 2022). The literature often explains user-level descriptions which support that students and teaching staff are ready to adopt CBEL, while institutional outcomes and readiness is less explored.

Second driver is institutional support and commitment that differentiates state of the adoption across countries. Studies such as Assalaarachchi et al. (2023), Njenga et al. (2019), and Shakor & Surameery (2021) reported moderate to high levels of adoption and repeatedly emphasized that the management commitment, technical support, training provision, and the presence of enabling policies are the main CBEL adoption enablers. While these enabling drivers are noticeable and vital, but selected literature highlights a distance between high levels of perceived satisfaction and actual adoption and progress. In some stronger movement from intention to actual adoption of CBEL is also demonstrated, but limited, specifically in developing countries' HEIs.

Economic and operational benefits emerged as a third adoption driver. This is why CBEL, which inherits cloud benefits, is repeatedly justified as a response to challenges of scalability, resource optimization, and cost pressure in HEIs (AlAjmi, 2023; Dima et al., 2023). It is because reasonable for institutions that their infrastructure overheads are reduced and the responsibility of provisioning and maintenance is shifted to cloud service providers. This enables universities to focus more teaching and learning (Aydin, 2021; El Mhouti et al., 2018). This argument is especially visible in the post-COVID research, where several studies report acceleration of CBEL continuity and cloud-based platform adoption (Bhardwaj et al., 2021; Eljak et al., 2024; Farah Ali et al., 2024). So a common and continuing point in these studies is that perceived cost advantage is a strong motivator, but it becomes fragile when bandwidth limitations, training costs, and cloud vendor lock are not considered and not planned well during the migration step.

Furthermore, in terms of specifics cloud service models, most of the studies selected simply label tools "cloud-based," without exploring specific models only explaining them in a general. Based on few studies that report adopted cloud service models summarized in Figure 3, Software as a Service (SaaS) models, such as Google Classroom and Microsoft 365, and others, lead among other models, demonstrating the practical use of learning management system (LMS) platforms.

Hybrid and federated cloud models are emerging in focused technical studies, indicating a growing interest in more sophisticated deployments, such as the deployment of virtual labs. In addition the PaaS and IaaS seem to be used less frequently, generally within broader adoption frameworks rather than standalone technical implementations.

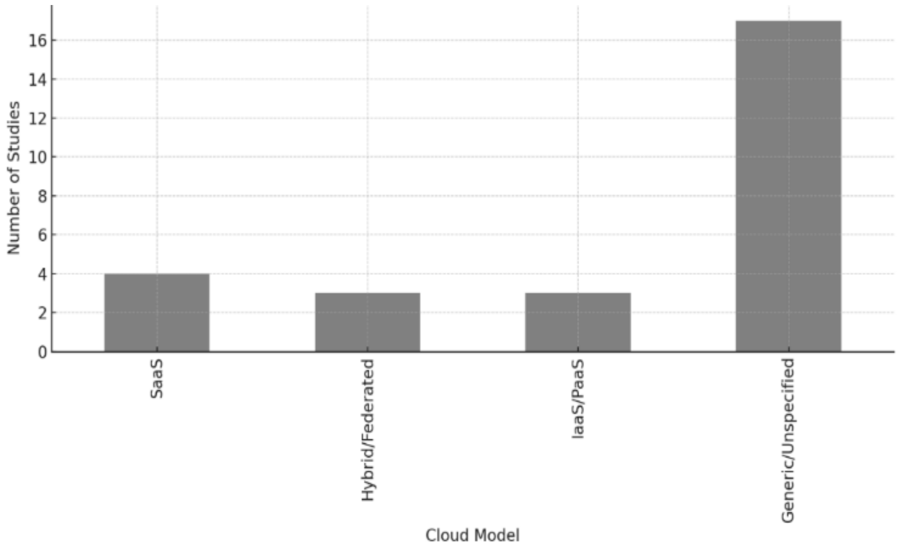

Fig. 3. Distribution of the CBEL solution considered in the literature

This evaluation of CBEL at the level of platform usage and user acceptance suggests that while CBEL adoption is widely discussed, deep technical exploration of PaaS and IaaS for e-learning remains partial and needs more specific empirical and experimental research. This helps explain why PEoU and PU dominate as drivers in many studies because the studied interventions are predominantly SaaS, rather than institutional on-promises cloud infrastructures, while infrastructural constraints, low skill, security issues, policy gaps, and integration and migration challenges consistently emerge as the main barriers to wider CBEL adoption.

Comparatively studies suggest that adoption drivers effects across contexts differently. In relatively better settings such as Malaysia, India, and Saudi Arabia, PU and PEoU are more likely to translate into actual system adoption because institutional support and digital infrastructure are stronger (Alajlan et al., 2020; Bhardwaj et al., 2021; Hussein & Hilmi, 2020). But similar positive perceptions in less prepared settings such as Ghana, Iraq, Libya, and Afghanistan, do not always lead to sustained adoption, because infrastructural and institutional readiness and support remain weaker (Al Ghawail et al., 2019; Armah & Ali, 2024; Barikzai et al., 2025). This suggests that in developing countries, user acceptance is necessary but not sufficient for successful CBEL adoption.

3.2 Adoption Barriers and Constraints

Across the chosen studies, barriers are not merely obstacles but constitute the boundary conditions that explain the intention to adoption gap. From the synthesis it can be specified that barriers are grouped to areas as shown in Figure 4. These barriers include infrastructure and connectivity constraints, security, privacy and trust limitations, skills and training deficits, and policy and regulation regarding its integration challenges are often interrelated rather than appearing independently. Figure 4 shows that infrastructure and connectivity barriers appear most frequently across studies, followed by security and training-related constraints.

Infrastructure and connectivity constraints dominate the barrier landscape in multiple developing contexts. Several studies highlight that limited bandwidth, unstable and low speed internet access, and unequal access to devices restrict adoption in under resourced areas and rural regions (Njenga et al., 2019; Thongsri et al., 2019). These limitations are important because it reframes adoption, as PU and PEOU are good enough in structural models, the practical ability to assess actual use of CBEL services can remain comparatively low. Where studies report low or initial adoption (e.g., Libya, Nigeria, parts of Iraq, Afghanistan), infrastructure weakness and funding gaps tend to be presented as primary constraints (Al Ghawail et al., 2019; Eze et al., 2020; Hashim et al., 2022). However technical approaches exist to address low-latency access and connectivity limitations such as Fog-Cloud techniques, but these remain underrepresented in research with empirical adoption (Larcher et al., 2021; Sood & Rawat, 2022).

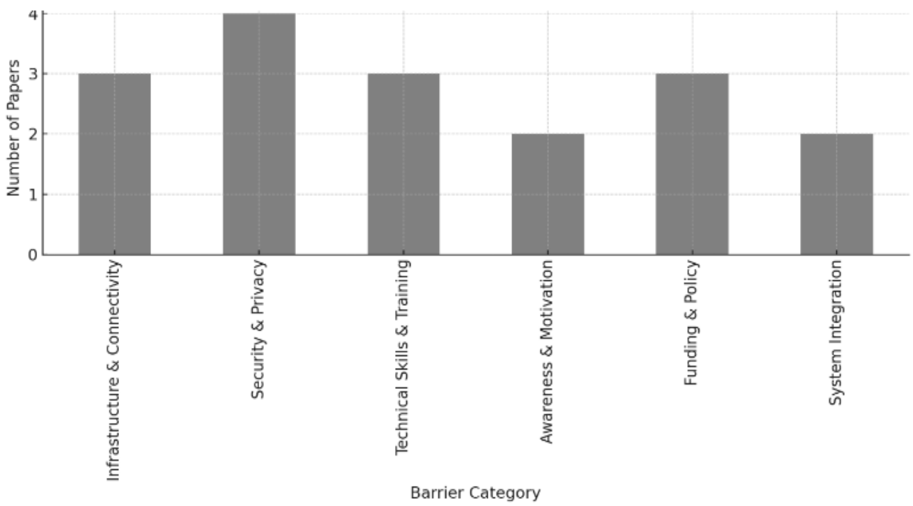

Fig. 4. Reported barriers frequency in the selected literature

Other barriers are security, privacy, and trust concerns that persistently raised in education settings due to student data and records, and institutional information importance. It is been repeatedly emphasized in the literature that confidentiality, integrity, identity management, authentication, compliance, and loss of direct control as major concerns in using cloud-based system (Khan & Salah, 2020; Wu & Plakhtii, 2021). It is critically synthesized that security is not only a technical risk, but also a trust and governance issue. This problem can exceed institutional commitment even when the user has positive attitude and high-level perception toward CBEL acceptance. This result is aligned with Feng et al. (2025), which shows that trust and perceived security risk are explicitly shown as vital factors for CBEL platform attitudes and actual adoption in HEIs, in all contexts.

Skills and training shortages are other barriers that have appeared. Bridging infrastructure and e-learning platform complexity constraints and acceptance outcomes, lack of technical skills among teaching staff and students, and weak institutional support structures for training are repeatedly reported as discouraging that actual adoption. This is true even when there is high intention to adopt CBEL (Eze et al., 2020; Njenga et al., 2019; Shahzad et al., 2020). The literature suggests that beside users' perception or technical design quality of the system, PEoU is socially influenced by training and support by organization. Hence, technical training and support act as essential, non-supplementary factor that assures successful and long-term CBEL adoption and transforming how users experience technology.

Other dimensions on barriers revealed are policy gaps, unclear institutional guidelines, integration complexity, and cloud vendor lock-in issues. These barriers are frequently reported in moderate and low adoption contexts also summarized in Table 1. It is suggested that when technology is adopted, infrastructure is improved, governance and interoperability become more visible constraints if not addressed from policy perspectives (Hussein & Hilmi, 2020; Kayali & Alaaraj, 2020; Qasem et al., 2020). Similarly, migration and interoperability concerns are important, and without adequate planning and regulation choices, CBEL adoption can lead to hidden costs, flexibility and dependency issues (Khan & Salah, 2020; Wu & Plakhtii, 2021). It is also highlighted that poor integration with existing systems and compatibility issues add technical complexity.

Other forms of digital gap and barriers in HEIs, specifically in developing countries, are also evidenced. Studies suggest that even if users show positive attitude to adopt CBEL in HEIs with weak connectivity, unstable or low funding, and limited technical capacity there is less of chance of sustainable CBEL over time (Njenga et al., 2019; Wang et al., 2026). This means that sustainability and long-term scalability are not only technical issues, but also institutional, technological, and regulatory readiness is vital. In this sense, CBEL adoption in developing countries is shaped by structural inequality as much as by technological choice. Reported barriers can be prioritized for future research on topics such as low-bandwidth solutions, regional CBEL adoption comparisons, integration models, and the need for training, which are recurring themes in selected literature.

3.3 Methods and Models of Assessing Adoption

The adoption of new technologies in social and organizational contexts is often associated with resistance and implementation challenges. In the case of CBEL, which is inherently a sociotechnical and multidisciplinary system (Lopes et al., 2022), adoption becomes more complex due to the interaction between user behavior, institutional readiness, and technological infrastructure. Therefore, many information system adoption models have been developed to provide a structured mechanisms for technology adoption assessment and prediction in organizational and social environments (Njenga et al., 2019). Some known adoption models reviewed by (Bhardwaj et al., 2021), (Srimadhaven et al., 2020), and (Cheng, 2022) are summarized and listed according to their temporal regression in Table 2.

Table 2: Chronological development of technology adoption known models.

No	Model	Year	Proposed by
1	Diffusion of Innovation (DOI)	1962	Rogers
2	Theory of Reasoned Action (TRA)	1977	Hill et al.
3	Expectation Confirmation Theory (ECT) or Expectation Disconfirmation Theory (EDT)	1980	Oliver
4	Technology Acceptance Model (TAM)	1986	Davis
5	Technology-Organization-Environment (TOE) Framework	1990	Tornatzky & Fleischer
6	Theory of Planned Behaviour (TPB)	1991	Ajzen
7	Adaptive Structuration Theory (AST)	1994	DeSanctis et al.
8	Social Cognitive Theory (SCT)	1995	Compeau et al.
9	Task–Technology Fit (TTF)	1995	Goodhue et al.
10	Knowledge-based view of the firm	1995	Grant et al.
11	Technology Readiness Index (TRI)	2000	Parasuraman
12	TAM2	2000	Venkatesh et al.
13	Cognitive Absorption Model	2000	Agarwal et al.
14	expectation-confirmation model (ECM)	2001	Bhattacherjee
15	Unified Theory of Acceptance and Use of Technology (UTAUT)	2003	Venkatesh et al.
16	Human, Organization, Technology (HOT) Fit	2008	Yusof
17	TAM3	2008	Venkatesh et al.

Most of these models can be applied across different domains such as mobile banking, e-commerce, e-government, and education. However, certain models are more suitable for assessing CBEL adoption in HEIs due to its sociotechnical nature and dependency on both user acceptance and institutional readiness (AlAjmi, 2023). While this historical overview is important, the review of the chosen studies shows that only some of these models are used in CBEL adoption assessment (Bhardwaj et al., 2021). In the selected studies, TAM and UTAUT dominate individual-level CBEL and e-learning adoption analysis in compare to TOE and IS success models as shown in Figure 5.

The distribution of theoretical models used in selected studies in Figure 5 shows a clear dominance of TAM and UTAUT-based approaches, indicating a strong focus on user perception and behavioral intention. In contrast, organizational and system-level models such as TOE and IS success models are less frequently applied, suggesting an imbalance in how adoption is evaluated.

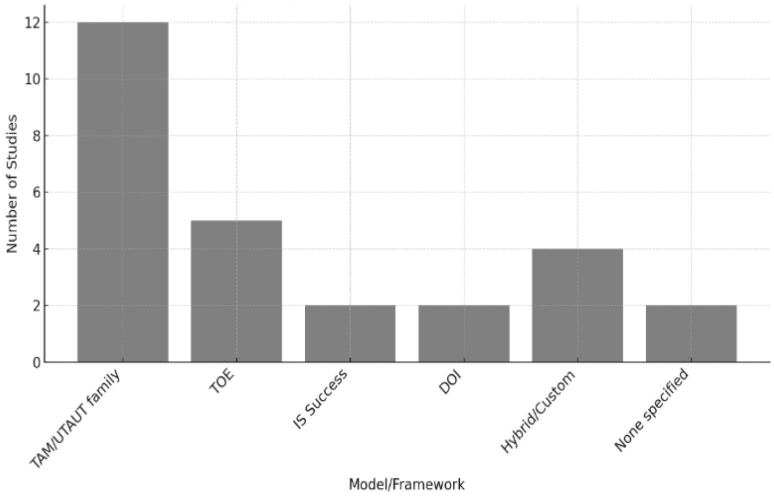

Fig. 5. Theoretical model adoption frequencies in the selected studies

Adoption models extracted from selected studies reflect the multi-dimensional nature of cloud-based e-learning adoption, where individual perception, institutional readiness, and system sustainability interact. Adoption models extracted are classified into the three categories as follow.

User Acceptance Assessment Models

User acceptance models focus on individual-level perceptions and behavioral intentions toward technology use, as TAM is the most popular in the reviewed studies. TAM explains adoption through PU and PEoU as main constructs that influence users' behavioral intent for adopting technology. In the CBEL context, PU is often associated with improved learning performance, flexibility, and accessibility, while PEoU reflects system usability and ease of interaction.

A study by Hussein & Hilmi (2020) used TAM to develop a conceptual model for adopting CBEL in Malaysian universities. In addition to PU and PEoU, security and trust, user needs, and innovativeness were also identified by selected studies as key factors influencing adoption. Their study further shows that students and teachers are more likely to adopt CBEL systems when they perceive clear benefits in satisfying their academic tasks and performance. Furthermore, technological readiness and access issues as a critical constraint were also highlighted, indicating that PU, PEoU cannot only ensure successful adoption. TAM2 and TAM3, as extensions of TAM, integrate additional factors including social influence, experience, and facilitating conditions, make the assessment model more suitable for complex and sociotechnical environments as HEIs. Similarly, constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions are integrated in UTAUT. As another cognitive and engaging aspect, which emphasize on experiential aspect of technology use, Agarwal & Karahanna (2000) emphasize that users are more likely to adopt information systems when they experience enjoyment, engagement, and immersion. It is inferred that in CBEL and developing context this suggests that course design, interactivity, and content quality are essential factors influencing adoption (Cheng, 2019).

These individual-level models, which focus on the overall understanding of user behavior, have limitations, despite their strengths (Bhardwaj et al., 2021). Despite they primarily focus on individual perception, they fail to study broader organizational and infrastructural bounds. This is significantly important, especially in developing countries, where adoption is heavily influenced by external factors beyond user control.

Organizational and Environmental Models

Organizational and environmental frameworks such as the TOE and DOI are normally used to address the limitations of user-centered models and have been adopted by several studies. TOE describes the assessment of technology adoption in three dimensions, including technological readiness (infrastructure, compatibility), organizational context (management support, resources), and environmental factors (policy, competition, vendor support). This model is relevant for CBEL in a low-resource context where institutional capacity and infrastructure significantly influence adoption decisions, and therefore some factors of TEO are included in the proposed model presented in section 3.6. In contrast the DOI theory focuses on innovative characteristics of a technology in a social context such as relative advantage, compatibility, complexity, trialability, and observability. In CBEL context DOI helps to assess how institutions evaluate the benefits and risks of its adopting explored for example in Kayali & Alaaraj (2020), and Bhardwaj et al. (2021).

The combination of TOE and DOI with other models were applied in many studies to provide a more comprehensive analysis. Bhardwaj et al. (2021) studied 304 public universities in India using an integrated TAM-TOE-DOI framework and found that competitive advantage, compatibility, technological readiness, leadership support, security concerns, and vendor support significantly influence adoption. Kayali & Alaaraj (2020) also used and integrated factors from DOI, with TAM and UTAUT on assessing the adoption of CBEL in Lebanese universities. In sum, the integration of these models allows for a more holistic understanding of adoption, capturing both user-level perceptions and institutional-level factors, which is important in developing contexts, as the adoption of CBEL and technology is not only a matter of user acceptance but also depends on infrastructure, policy, and support from the organization.

Post-Adoption Continuance and Success Assessment Models

In the selected literature, generally fewer studies address post-adoption assessment, in compare to studies focusing on initial adoption. The expectation-confirmation model (ECM) is used in some studies to assess continuance intention and user satisfaction, as in Cheng (2020). This model explains adoption as a process in which users' evaluation takes place if their expectations are confirmed after using the system using key constructs (e.g., confirmation, PU, satisfaction, and continuance intention). Cheng (2019) demonstrated that course design quality significantly influences students' PU and over satisfaction, which ultimately impacts their intention to continue using CBEL platform. In the same way, Kayali & Alaaraj (2020) emphasized that user satisfaction is a critical predictor of behavioral intention, suggesting that adoption should be viewed as an ongoing process rather than a one-time decision or only initial adoption.

To summarize, the analysis of literature on adoption models exposes a result that most studies rely severely on user acceptance models such as TAM and UTAUT, focusing on PU and PEoU. Whereas these models effectively explain user intention, they are inadequate in addressing the broader challenges associated with CBEL adoption in developing countries. In contrast, organizational models such as DOI, especially TOE, provide a more comprehensive perspective by incorporating institutional and environmental factors. The result, however, shows that these models are less frequently applied. Furthermore, post-adoption models such as ECM are also untapped, despite their importance for understanding long-term system sustainability. This imbalance suggests a critical gap in literature as studies tend to emphasize more on individual perception but marginalizing organizational readiness and long-term outcomes. These findings directly inform the development of an integrated framework focusing on both sides which is presented in section 3.6.

3.4 Impact Measures and Reported Outcome

Sensitized across multiple studies, the impact of CBEL was mainly assessed through perceptual and intention-based factors. The most frequently used measures are PU, PEoU, BI, user satisfaction, and continuance intention, illustrated in Figure 6. Most measuring factors are for examining user acceptance and readiness, especially in studies grounded in TAM and UTAUT, but most evidence shows they do not reflect actual system use and objective educational outcomes.

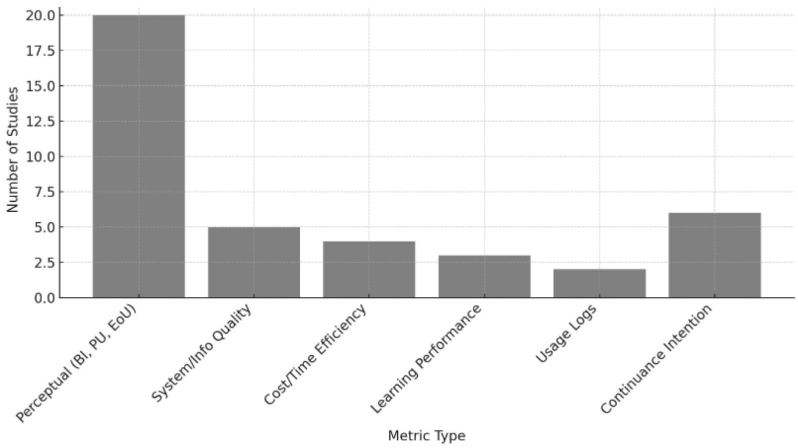

Fig. 6. Frequency of measurements and factors used in studies

Most studies are based on subjective user-level measures rather than objective indicators such as actual system usage, learning analytics, academic performance, retention, or cost benefit outcomes as depicted in Figure 6. For example, Thongsri et al. (2019) found that performance expectancy, social influence, and system quality related factors strongly affect students' motivation and intention to adopt and use an LMS with cloud capabilities. Similarly, Maisha & Shetu (2023) reported strong post pandemic student willingness to use e-learning platforms in Bangladesh, while Farah Ali et al. (2024) showed that both institutional and student perspectives recognized positive effects of e-learning adoption in HE. These studies indicate that users generally recognize the value of cloud-supported learning environments when they are accessible and usable. What emerges from this sequence is that the current literature explains user perception more effectively in compare to actual adoption and continuing institutional outcomes. Similarly, a gap between positive intention and measurable outcomes has emerged from the synthesis as in many developing countries, users may report high readiness, which does not always lead to sustainable CBEL use or learning benefits. Findings by Njenga et al. (2019) and Eze et al. (2020) also show that even with users' positive attitudes, actual implementation is affected by technical and organizational limitations. In addition, actual use and outcomes-based factors are rarely assessed as a Gupta et al. (2022) reported that CBEL can improve engagement and collaboration in Indian higher education, if factors such as system and information quality, service quality, net benefits, learning performance, flexibility, collaboration, and user experience are considered. Sharma et al. (2025) further recommend knowledge management and institutional readiness for enhancement in academic results supported by CBEL adoption. These findings move beyond only acceptance and orient to actual educational value. Yet such measures are still much less common than PU, PEoU, and BI in the field.

Moreover, the contextual difference in reported outcomes across countries becomes evident. In relatively prepared contexts as Malaysia, India, and Saudi Arabia, outcomes are not only reported to intention, but also include improved collaboration, access to learning materials, user experience, and in some cases better learning performance are assessed. Conversely, in less prepared contexts such as Libya, Nigeria, Iraq, and Afghanistan, impact assessment persists closer to readiness, intention, or pilot level acceptance (Barikzai et al., 2025; Maisha & Shetu, 2023; Sharma et al., 2025). This outcome implies that impact measures are not only determined by the assessment model used, but also by the quality of digital infrastructure and institutional support available in each setting.

In addition to contextual differences, the empirical data across studies are mainly based on cross-sectional and self-reported surveys focusing on acceptance intention, but less on sustainable CBEL, organizational outcomes, and strategic benefits. This shows that current evidence may overemphasize adoption success by aligning intention with outcome or impact. It is recommended for future research to focus on objective, longitudinal factors, such as actual usage data, completion rates, satisfaction over time, learning analytics, and institutional performance measures, to provide a more complete understanding of CBEL outcomes in developing countries.

Altogether, the reviewed studies show that CBEL can result in positive outcomes in terms of flexibility, accessibility, collaboration, and satisfaction, but the literature still lacks balanced measurement of long-term and institution-level impacts. To address these limitations, the need for an integrated assessment framework that connects user acceptance with organizational readiness and measurable outcomes becomes apparent, which is presented in the subsequent section.

3.5 Summary of the Review and Research Gaps

Recurring patterns that shape CBEL adoption in developing countries are summarized as main themes, including adoption drivers, barriers, assessment models, and reported outcomes presented in previous subsections. Several gaps were also revealed that limit both theory development and practical adoption and implementation of CBEL in developing nations. Based on the review, the following points can be derived and categorized in four directions.

Adoption drivers and enabling conditions

- PU, PEoU, and flexibility remain strong user-level drivers in most studies, especially in contexts where cloud platforms are already visible and accessible (Hussein & Hilmi, 2020; Maisha & Shetu, 2023).
- But, user-level drivers are more effective in developing contexts if they are supported by institutional readiness, infrastructure, training, and management support (Bhardwaj et al., 2021; Njenga et al., 2019).
- Thus, user willingness alone is not enough for sustainable adoption, the organizational, technical and environmental factors are also vital in low-resource contexts.

Adoption barriers and contextual constraints

- The main barriers revealed are weak infrastructure, unstable connectivity, security and privacy concerns, limited technical skills, and policy or integration (Eze et al., 2020; Hashim et al., 2022; Khan & Salah, 2020).
- Barriers are not isolated, and they interact with each other and often reflect wider digital inequality in different developing countries' higher education systems (Njenga et al., 2019; Wang et al., 2026). As a result, with weak institutional and regulatory readiness, the success and sustainability of CBEL remain difficult.

Models used to assess adoption

- User-based models (e.g., TAM and UTAUT) were commonly relied on BI, PU, and PEoU (Hussein & Hilmi, 2020; Thongsri et al., 2019). On the other hand, fewer studies reported using organizational and environmental models such as TOE or integrated models such as TAM–TOE–DOI, even if these are more suitable for developing countries, where infrastructure, management support, and regulation matter strongly (Bhardwaj et al., 2021; Kayali & Alaaraj, 2020).
- This methodological imbalance in the literature shows that perception is measured more often than organizational and institutional readiness.

Impact measures and reported outcomes

- Common in the reviewed studies were the perceptual indicators, including PU, PEoU, behavioral intention, and satisfaction, but few studies measured actual use, learning performance, or outcomes (Cheng, 2019; Gupta et al., 2022).
- Collaboration, user experience, and in some cases academic improvement were reported outcomes in relatively prepared contexts, but in low prepared contexts, results and outcomes persist closer to readiness or pilot-level adoption (Njenga et al., 2019; Sharma et al., 2025). It shows that current evidence still explains intention better than long-term educational and institutional effectiveness.

To summarize, several research gaps become clear from the above synthesis. First, the selected literature is heavily weighted toward user acceptance and intention-oriented explanations, but organizational, infrastructural, and environmental conditions are less integrated. Second, many studies in the context of HEIs in developing countries are cross-sectional and based on self-reported perceptions, which limit understanding of actual use, sustainability, and long-term success. Third, the lack of enough context-sensitive models that explain how user readiness, institutional support, and technological capacity interact under the specific constraints of developing nations is evident in the literature. Finally, sustainability, scalability, and outcome-based success evidence are remained limited, especially in institutions facing digital inequality, weak policy support, and limited resources.

Overall, these findings suggest that CBEL adoption in developing countries should not be taken only as a user-level technology acceptance issue, but it should also be considered a broader sociotechnical and institutional process formed by individual, organizational, and infrastructural factors in combination. These summary insights and research gaps provide the basis for the proposed adoption framework presented in the next subsection.

3.6 Proposed Framework

Here, a framework is proposed to assess CBEL adoption in HEIs in developing countries. The framework is grounded in a synthesis of the review and research gaps identified in the previous subsection. Common patterns and gaps build the dimension and specific and measurable factors of HEIs in developing countries. The framework in Figure 7 translates the main review themes to specific quantifiable constructs and their relationships, which echo adoption conditions frequently reported in developing nations. The framework demonstrates link between institutional and technological readiness, and user acceptance or individual level factors, and the actual adoption.

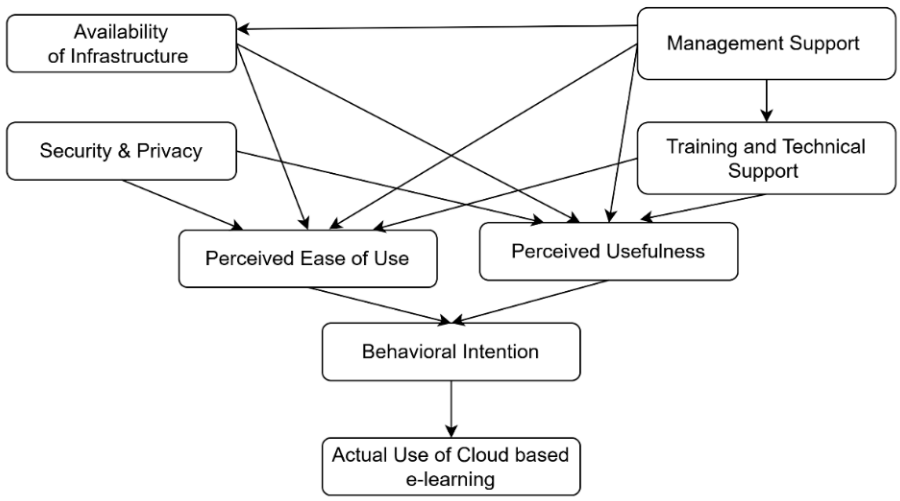

Fig. 7. Proposed CBEL adoption assessment framework

The importance of technological and organizational readiness was constantly stressed by the literature (e.g., Njenga et al. (2019), Hashim et al. (2022), and Eljak et al. (2024)) that forms the adoption of CBEL in developing countries. The proposed framework therefor considers technological readiness in terms of infrastructure availability (IA) and security and privacy (SP), whereas organizational readiness is characterized using management support (MC) and training and technical support (TTS) also explained by Assalaarachchi et al. (2023), Shakor & Surameery (2021), and Bhardwaj et al. (2021). These four factors as the most significant enablers or barriers if not exist, also frequently appeared in the reviewed studies, and were therefore included in the framework to address these challenges in developing contexts.

The framework also includes perceived ease of use (PEoU), perceived usefulness (PU), and behavioral intention (BI) as core user-level constructs from TAM. This is aligned with studies based on TAM and UTAUT such as in e.g., Hussein & Hilmi (2020), Cheng (2020), and Kayali & Alaaraj (2020), but the model extends beyond this and includes institutional and infrastructural factors. In the proposed model, IA, SP, MS, and TTS are predicted to form users' perceptions of ease of use and usefulness, which then influence behavioral intention (BI), and ultimately lead to the adoption and actual use (AU) of CBEL. Though the above factors focus on the adoption stage assessment, the BI and AU constructs reflect the intention and actual use or post-adoption assessment. BI and AU may focus on CBEL adoption outcomes, continuance intention, satisfaction, or overall learning improvement and academic performance (Farah Ali et al., 2024; Gupta et al., 2022; Sharma et al., 2025). These factors are important to shift the focus from initial acceptance to actual use and to educational and learning values.

In addition to direct relationships between factors, such as the impact of management support on users' perceptions (PEoU, and PU), the proposed framework also highlights indirect impacts of the management support on users' perception by improving infrastructure provision, training opportunities, and technical support. This is why the framework reflects the supportive role of MC in strengthening both institutional readiness and user adoption conditions.

In comparison to other models based on user perception, the proposed framework includes a more holistic and sensitive to developing context factors. It is evident in the review that even if users report positive attitudes and high behavioral intention, actual adoption of CBEL may remain partial or limited, due to low infrastructure, security issues, poor technical support, and insufficient institutional commitment, which is aligned with Njenga et al. (2019), Hashim et al. (2022), and Eljak et al. (2024). Hence, the framework is designed in a way that not only focuses on individual acceptance, but also the relationship between user-level, organizational, and infrastructural related factors that led to CBEL adoption, aligned with Al-Sharafi et al. (2021), Bhardwaj et al. (2021), and Kayali & Alaaraj (2020) that suggested integrated models.

To conclude on the proposed framework, collectively, it reflects the SLR. The model explains that in developing countries, successful CBEL adoption depends not only on users' positive intention of system usefulness and ease of use, but also on how HEIs can provide the infrastructure, security, policy, management support, and training required for successfully transforming BI to AU. Thus, this model is more relevant for future empirical assessments in HEIs in developing countries such as Afghanistan and similar contexts, where institutional and infrastructural limitations need to be taken together with user-level perceptions. In this manner, a practical and theoretical base is formed by the framework for investigating how technological readiness, institutional support, and user acceptance altogether led to actual use of CBEL in contexts of limited resources and diverse institutional environments.

4. Study Implications

The study theoretically implies that the adoption of CBEL in developing countries cannot be explained only through factors of user acceptance and intention. Even though PU, PEoU, and BI are important, but infrastructure readiness, management support, technical training, security, and policy support also play vital roles, specifically in a developing context. Thus, it is recommended that future research on CBEL in the context of HEIs in developing countries should not only focus on user-level factors, but also on more integrated sociotechnical models that combine individual, organizational, and technological aspects.

From a practical perspective, this systematic review directs that decision makers in higher education, ICT administrators, and policymakers should not see CBEL only as a digital tool for teaching and learning, but as a broader institutional system that requires investment in infrastructure, technical support, governance, and continuous technology skills improvement.

5. Conclusion

This study systematically reviewed empirical research on cloud-based e-learning (CBEL) adoption in higher education institutions (HEIs) in developing nations. Using PRISMA process the review shows that CBEL has become increasingly important in HEIs because it gives many benefits such as flexibility, accessibility, and scalability, especially after the COVID-19 period. The evidence also shows that adoption in developing countries HEIs remains uneven and cannot be explained only through user positive perception of technology. In the reviewed studies, users generally show high readiness and positive intention to use CBEL, but actual implementation depends heavily on institutional and contextual factors such as infrastructure availability, stable connectivity, management support, technical training, policy support, and security conditions. It is also found that literature is dominated by perception-oriented studies and mostly cross-sectional, and with strong focus on user-level acceptance models such as TAM and UTAUT. While these models are useful in explaining intentions, they are less effective in capturing organizational, environmental and infrastructural factors in developing countries. In addition, the review found that outcome assessment is still largely based on subjective indicators such as PEoU, PU, satisfaction, and BI, but less focus on long-term academic and organizational outcomes, and overall success of CBEL. To address these limitations, this study proposed an integrated framework that includes technological readiness, organizational support, user acceptance, and CBEL actual use and outcomes. The framework provides a more appropriate basis for context sensitive future assessment of CBEL adoption in HEIs of developing countries. Particularly in low resource environment such as Afghanistan. Overall, the study confirms that the main challenge in many developing nations is no longer whether users value CBEL, but also how institutions can provide the structural and policy conditions necessary to transform intention into effective and sustainable adoption.

This study has many limitations. It is restricted to Scopus and WoS databases and to the period 2019-2025. In addition, most studies are cross-sectional and self-reported survey data, overemphasized on PU and intention rather than actual system use and CBEL success. Another limitation is that selected studies are mostly on SaaS model of e-learning platforms, but not on other cloud models such as PaaS and IaaS. Additionally, due to contextual diversity of developing countries generalization of findings are difficult, as infrastructure, policy environments, and institutional readiness vary significantly between regions. So, future works can focus on longitudinal and empirical studies that integrate behavioral, organizational, and technical analysis, including actual system usage statistics and logs, learning performance metrics, and institutional success. Future studies can also explore other cloud services and deployment models, edge/fog computing, and AI-supported and cloud assisted learning platforms in improving accessibility and performance in low resource environments. Lastly the proposed framework can be validated and refined using mixed methods for its applicability as a tool for assessing CBEL adoption HEIs in developing nations.

References

Abdekhoda, M., Dehnad, A., & Zarei, J. (2022). Factors influencing adoption of e-learning in healthcare: integration of UTAUT and TTF model. *BMC Medical Informatics and Decision Making, 22*(1). https://doi.org/10.1186/S12911-022-02060-9

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly: Management Information Systems*, *24*(4), 665–694. https://doi.org/10.2307/3250951

Aini, Q., Budiarto, M., Putra, P. O. H., & Rahardja, U. (2020). Exploring E-learning Challenges During the Global COVID-19 Pandemic: A Review. *Jurnal Sistem Informasi*, *16*(2), 57–65. https://doi.org/10.21609/jsi.v16i2.1011

Al Ghawail, E. A., Ben Yahia, S., & Alrshah, M. A. (2019). Challenges of Applying e-learning in the Libyan Higher Education system. *International Journal of Advanced Trends in Computer Science and Engineering*, *8*(1), 38–43. https://doi.org/10.30534/ijatcse/2019/0681.42019

Alajlan, N., Hadwan, M., & Ibrahim, D. M. (2020). Effectiveness of Adopting Cloud-Based E-Learning at Qassim University. *The Computer Journal*, *65*(5), 1098–1106. https://doi.org/10.1093/COMJNL/BXAA146

AlAjmi, Q. (2023). Adoption Model for Cloud-Based E-Learning in Higher Education. *The International Conference of Advanced Computing and Informatics, 179*, 574–584. https://doi.org/10.1007/978-3-031-36258-3_51

Al-Hajri, S., Echchabi, A., Ayedh, A. M., Mispah, M., & Omar, S. (2021). The Cloud Computing Systems' Adoption in the Higher Education Sector in Oman in Light of the COVID-19 Pandemic. *International Journal of Evaluation and Research in Education*, *10*(3), 930–937. https://doi.org/10.11591/ijere.v10i3.21671

Al-Sharafi, M. A., AlAjmi, Q., Al-Emran, M., Qasem, Y. A., & Aldheleai, Y. M. (2021). Cloud Computing Adoption in Higher Education: An Integrated Theoretical Model. In *Recent advances in technology acceptance models and theories* (Vol. 335, pp. 191–209). Springer International Publishing. https://doi.org/10.1007/978-3-030-64987-6_12

Armah, E. D., & Ali, I. S. (2024). A Comprehensive Analysis of Faculty Adoption of Cloud Computing E-Learning in Ghanaian Technical Universities. *International Journal of Engineering Pedagogy*, *14*(5), 65–87. https://doi.org/10.3991/ijep.v14i5.47841

Assalaarachchi, L., I, A. L., & P K H, S. K. (2023). Adoption of Software-as-a-Service (SaaS) Applications in E-learning: Perception of the Management Undergraduates in a Selected State University of Sri Lanka. *Journal of Business Research and Insights (Former Vidyodaya Journal of Management)*, *9*(II), 57–77. https://doi.org/10.31357/VJM.V9III.6588

Aydin, H. (2021). A Study of Cloud Computing Adoption in Universities as a Guideline to Cloud Migration. *SAGE Open*, *11*(3). https://doi.org/10.1177/21582440211030280

Barikzai, S., Bharathi S, V., & Perdana, A. (2025). Digital learning initiatives forging inclusive education in post-conflict nations. *Cogent Education*, *12*(1). https://doi.org/10.1080/2331186X.2025.2457904

Bhardwaj, A. K., Garg, L., Garg, A., & Gajpal, Y. (2021). E-Learning during COVID-19 Outbreak: Cloud Computing Adoption in Indian Public Universities. *Computers, Materials and Continua*, *66*(3), 2471–2492. https://doi.org/10.32604/cmc.2021.014099

Cheng, Y. M. (2019). How does task-technology fit influence cloud-based e-learning continuance and impact? *Education and Training*, *61*(4), 480–499. https://doi.org/10.1108/ET-09-2018-0203

Cheng, Y. M. (2020). Students' satisfaction and continuance intention of the cloud-based e-learning system: roles of interactivity and course quality factors. *Education and Training*, *62*(9), 1037–1059. https://doi.org/10.1108/ET-10-2019-0245

Dima, A., Bugheanu, A. M., Boghian, R., & Madsen, D. Ø. (2023). Mapping Knowledge Area Analysis in E-Learning Systems Based on Cloud Computing. *Electronics (Switzerland)*, *12*(1). https://doi.org/10.3390/electronics12010062

El Mhouti, A., Erradi, M., & Nasseh, A. (2018). Using cloud computing services in e-learning process: Benefits and challenges. *Education and Information Technologies*, *23*(2), 893–909. https://doi.org/10.1007/s10639-017-9642-x

Eljak, H., Ibrahim, A. O., Saeed, F., Hashem, I. A. T., Abdelmaboud, A., Syed, H. J., Abulfaraj, A. W., Ismail, M. A. Bin, & Elsafi, A. (2024). E-Learning-Based Cloud Computing Environment: A Systematic Review, Challenges, and Opportunities. *IEEE Access*, *12*, 7329–7355. https://doi.org/10.1109/ACCESS.2023.3339250

Elmasry, M. A., & Ibrahim, M. H. (2021). Cloud computing for e-learning: A proposed model for higher education institutions in developing countries. *International Journal of Scientific & Technology Research*, *10*(4), 408–416.

Eze, S. C., Chinedu-Eze, V. C. A., Okike, C. K., & Bello, A. O. (2020). Factors influencing the use of e-learning facilities by students in a private Higher Education Institution (HEI) in a developing economy. *Humanities and Social Sciences Communications*. https://doi.org/10.1057/s41599-020-00624-6

Farah Ali, A., Haji Abdullah, R., Abi Hassan, A., Osman Abdullahi, H., & Mohamud Mohamed, M. (2024). COVID-19 Pandemic Impact on E-Learning Adoption and Its Utilization at Higher Education: A Comparative Analysis of Institutions and Students' Perspectives. *Ingénierie Des Systèmes d'Information*, *29*(2), 447–457. https://doi.org/10.18280/isi.290206

Feng, J., Yu, B., Tan, W. H., Dai, Z., & Li, Z. (2025). Key factors influencing educational technology adoption in higher education: A systematic review. *PLOS Digital Health*, *4*(4). https://doi.org/10.1371/JOURNAL.PDIG.0000764

Gupta, N., Sharma, N., & Sood, S. (2022). Empirical Analysis on Parameters for Adoption of Cloud-Based e-learning in Indian Higher Education System: A User's Perspective. In A. Joshi, M. Mahmud, R. G. Ragel, & N. V. Thakur (Eds.), *Information and Communication*

Technology for Competitive Strategies (ICTCS 2020) (Vol. 191, pp. 977–991). Springer. https://doi.org/10.1007/978-981-16-0739-4_91

Hashim, H. S., Salah, A. A., & Al-Sulami, Z. A. (2022). Hinders of Cloud Computing Usage in Higher Education in Iraq: A Model Development. *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, *10*(3), 707–714. https://doi.org/10.52549/IJEEI.V10I3.3908

Hussein, L. A., & Hilmi, M. F. (2020). Cloud Computing Based E-learning in Malaysian universities. *International Journal of Emerging Technologies in Learning*, *15*(8), 4–21. https://doi.org/10.3991/IJET.V15I08.11798

Kayali, M., & Alaaraj, S. (2020). Adoption of Cloud Based E-learning in Developing Countries: A Combination of DOI, TAM and UTAUT. *International Journal of Contemporary Management and Information Technology*, *1*(1), 1–7. www.ijcmit.com

Khan, B. H. (2005). *Managing e-learning: Design, delivery, implementation, and evaluation*. IGI Global.

Khan, M. A., & Salah, K. (2020). Cloud adoption for e-learning: Survey and future challenges. *Education and Information Technologies*, *25*(2), 1417–1438. https://doi.org/10.1007/s10639-019-10021-5

Kumar, J. A., Bervell, B., & Osman, S. (2020). Google classroom: insights from Malaysian higher education students' and instructors' experiences. *IJCSNS*, *25*(5), 4175–4195. https://doi.org/10.1007/S10639-020-10163-X

Kumar, R. (2023). Usage of Cloud Computing Application by Students from Kurukshetra University: the Current State and Perspectives. *JIOS*, *47*(1), 189–201. https://doi.org/10.31341/jios.47.1.11

Larcher, L., Ströele, V., & Dantas, M. (2021). A cloud-based system for distance learning supported by Fog-Cloud cooperation. *International Journal of Grid and Utility Computing*, *12*(5–6), 618–634. https://doi.org/10.1504/IJGUC.2021.120114

Lopes, C., Bernardes, Ó., Gonçalves, M. J. A., Terra, A. L., da Silva, M. M., Tavares, C., & Valente, I. (2022). E-Learning Enhancement through Multidisciplinary Teams in Higher Education: Students, Teachers, and Librarians. *Education Sciences*, *12*(9). https://doi.org/10.3390/educsci12090601

Maisha, K., & Shetu, S. N. (2023). Influencing factors of e-learning adoption amongst students in a developing country: the post-pandemic scenario in Bangladesh. *Future Business Journal*, *9*(1), 1–16. https://doi.org/10.1186/S43093-023-00214-3

Malkawi, A. R., Bakar, M. S. A., & Dahlin, Z. M. (2024). Cloud-Based Virtual Learning Environment Model: A Delphi Study. *Law, State and Telecommunications Review*, *16*(1), 1–24. https://doi.org/10.26512/lstr.v16i1.47890

Matthew, U., Kazaure, J., Cloud, N. O.-E. E. Trans., & 2021, undefined. (2021). Contemporary development in E-Learning education, cloud computing technology & internet of things. *EAI Endorsed Transactions on Cloud Systems*, *7*(20). https://doi.org/10.4108/eai.31-3-2021.169173

Muhisn, Z. A. A., Hamid, S. A., Noori, A. S., & Muhisn, S. A. (2023). Cloud Computing Services in Higher Education in Iraqi Universities. *International Journal of Intelligent Systems and Applications in Engineering*, *11*(6s), 669–673. https://www.ijisae.org/index.php/IJISAE/article/view/2902

Njenga, K., Garg, L., Bhardwaj, A. K., Prakash, V., & Bawa, S. (2019). The cloud computing adoption in higher learning institutions in Kenya: Hindering factors and recommendations for the way forward. *Telematics and Informatics*, *38*, 225–246. https://doi.org/10.1016/j.tele.2018.10.007

Page, M. J., Joanne, E. M., Isabelle, B., Tammy, C. H., Cynthia, D. M., & Larissa, S. et al. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *Bmj*, *10*(1). https://doi.org/10.1186/s13643-021-01670-0

Pokhrel, S., & Chhetri, R. (2021). A Literature Review on Impact of COVID-19 Pandemic on Teaching and Learning. *Higher Education for the Future*, *8*(1), 133–141. https://doi.org/10.1177/2347631120983481

Qasem, Y., Abdullah, R., Yaha, Y., Sciences, R. A.-A., & 2020, undefined. (2020). Continuance use of cloud computing in higher education institutions: A conceptual model. *Applied Sciences*, *10*(19). https://doi.org/10.3390/app10196628

Rehaimi, A., Sadqi, Y., Maleh, Y., Gaba, G. S., & Gurtov, A. (2024). Towards a federated and hybrid cloud computing environment for sustainable and effective provisioning of cyber security virtual laboratories. *Expert Systems with Applications*, *252*. https://doi.org/10.1016/j.eswa.2024.124267

Shahzad, F., Xiu, G. Y., Khan, I., Shahbaz, M., Riaz, M. U., & Abbas, A. (2020). The moderating role of intrinsic motivation in cloud computing adoption in online education in a developing country: a structural equation model. *Asia Pacific Education Review*, *21*(1), 121–141. https://doi.org/10.1007/s12564-019-09611-2

Shakor, M. Y., & Surameery, N. M. S. (2021). Cloud Computing Technologies Adoption in Higher Education Institutes During COVID-19 Pandemic: Case Study. *Passer Journal of Basic and Applied Sciences*, *3*(2), 187–193. https://doi.org/10.24271/PSR.31

Sharma, M., Vadalkar, S., Singh, A., Chavan, G., & Tsagarakis, K. P. (2025). How Does Cloud Computing Adoption Accelerate Education?-Enhancing Academic Results by Integrating Knowledge Management Pre and Post Pandemic. *International Journal of Human-Computer Interaction*. https://doi.org/10.1080/10447318.2024.2440673

Sood, S. K., & Rawat, K. S. (2022). Fog-assisted virtual reality-based learning framework to control panic. *Expert Systems*, *39*(4). https://doi.org/10.1111/exsy.12700

Srimadhaven, T., Chris Junni, A. V., Harshith, N., Jessenth Ebenezer, S., Shabari Girish, S., & Priyaadharshini, M. (2020). Learning analytics: Virtual reality for programming course in higher education. In J. K. R., J. L., & N. S.V. (Eds.), *Procedia Computer Science* (Vol. 172, pp. 433–437). Elsevier B.V. https://doi.org/10.1016/j.procs.2020.05.095

Sugandini, D., Istanto, Y., Arundati, R., & Adisti, T. (2022). Intention to Adopt E-Learning with Anxiety: UTAUT Model. *Review of Integrative Business and Economics Research*, *11*, 198–212.

Thongsri, N., Shen, L., & Bao, Y. (2019). Investigating factors affecting learner's perception toward online learning: evidence from ClassStart application in Thailand. *Behaviour and Information Technology, Taylor & Francis*, *38*(12), 1243–1258. https://doi.org/10.1080/0144929X.2019.1581259

Wang, T., Dai, T., Yang, L., Osmanova, L., & Hwarari, D. (2026). Digital innovation in higher education: comparing approaches in developed and developing countries. *Frontiers in Education*, *10*, 1723087. https://doi.org/10.3389/feduc.2025.1723087

Wu, W., & Plakhtii, A. (2021). E-Learning Based on Cloud Computing. *International Journal of Emerging Technologies in Learning*, *16*(10), 4–17. https://doi.org/10.3991/ijet.v16i10.18579