JOURNAL OF COMPUTATIONAL INNOVATION AND ANALYTICS
https://e-journal.uum.edu.my/index.php/jcia

How to cite this article:
Mannan, M., Maruf, T. I., Ni, J., & Asaduzzaman, M. (2026). Predicting adoption of AI-driven e-learning systems in Bangladesh's public higher education: A survey-based machine learning approach. *Journal of Computational Innovation and Analytics*, *5*(2), 47-62. https://doi.org/10.32890/jcia2026.5.2.3

Predicting adoption of AI-driven e-learning systems in Bangladesh's public higher education: A survey-based machine learning approach

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Received: 07/03/2026 Revised: 05/06/2026 Accepted: 28/06/2026 Published: 31/07/2026

ABSTRACT

Over the last few years, the rapid growth of information technology (IT) has changed how digital learning systems are integrated into public higher education systems. There still seems to be a lack of understanding of the factors that affect the successful implementation of artificial intelligence (AI)-driven systems in public higher education systems. Due to inadequate infrastructure, varying levels of digital literacy among users, and a lack of empirically based models to predict system outcomes, many public higher education systems have been unable to implement AI-driven systems in their eLearning environments. This paper aims to take the first step toward developing a predictive model of AI-driven eLearning system adoption. To do this, a machine learning approach will be used to develop the model. This study employed a fully quantitative method involving 287 academic staff and students from five public higher education institutions in Bangladesh. The findings identified three factors of the Institutional eLearning Framework as the most significant predictors of eLearning adoption: perceived usefulness of eLearning, institutional support, and data quality of the eLearning system. The main contribution of this study to the body of research on the higher education system is to link one or more established theories of acceptance with predictive analysis models, thereby developing a tool that can be put in the hands of a system planner.

Keywords: Adoption, AI-driven eLearning, machine learning, predictive model, public higher education

INTRODUCTION

Learning has become digital. Over the last 2-3 decades, several advancements in information technology have enabled learning at any time and from anywhere. Various technologies, such as MOOCs and AI, help create greater flexibility and personalization in learning (Yuan & Hu, 2025). In developing countries, due to educational inequalities, providing technology is of utmost importance, as it helps expand educational access and equity (Fakoyede et al., 2026). With focused digital development, such as the Digital Bangladesh Initiative, Bangladesh is well-poised to transform education (Rahman & Hossain, 2025). However, the implementation of AI in public universities' e-learning platforms is still pending.

While there is considerable enthusiasm for AI technologies and their positive effects on learning and teaching, educational know-how at regional universities remains lacking (Mannan et al., 2025). This study aims to fill this gap by exploring the determinants of AI adoption in higher educational institutions in Bangladesh and developing a model to predict frameworks for operational adoption.

Background to the Study

Among the world's leading eLearning platforms, advanced technology, particularly Artificial Intelligence, has been integrated to improve learning personalization, learning flexibility, and the automation of feedback and feedback collection. Customized learning materials are combined with the adaptability of the AI algorithm, allowing students to navigate and master them at their own pace and instructional level (Mannan & Maruf, 2025). Additionally, to support students, AI chatbots are designed to answer administrative and student inquiries.

Amid a growing number of students and educators and more than 40 publicly funded universities, Bangladesh's public universities are shaping the future of the nation's higher education system and services through innovation and research. Though Bangladesh's public universities offer rudimentary digital learning systems, such as online courses and digital libraries, the adoption of Artificial Intelligence (AI) learning systems is almost absent (Sultana & Faruk, 2024). Even as the Government of Bangladesh initiates the Digital Bangladesh plan, the education sector remains largely undeveloped in terms of digitization (Mannan et al., 2023).

It has also been suggested that without satisfying the students' and educators' most pressing needs, integrated digital learning systems will continue to penetrate universities almost not at all. Public universities in Bangladesh are facing the challenge of improving the effectiveness and success of integrated digital learning systems. There is still concern about the adoption of integrated digital learning systems in public universities as AI learning systems are added to them.

Problem Statement

The growing digital learning systems here in Bangladesh have yet to see mainstream application of AI-based e-learning in public higher education institutions (Enny et al., 2025). Focusing on AI technologies, investments have proven to be in vain due to low interaction, as both students and instructors oppose their use. Other institutes have remained AI-deficient due to a lack of knowledge, specifically about the driving forces behind successful integrations of such systems. The developing world, particularly Bangladesh, faces unique obstacles that render the adoption of technology, as cited in most research and technology adoption literature, almost useless (Maruf et al., 2024). It is unfortunate to waste limited resources on technologies that do not contribute to better learning, while failing to address the digital divide across educational institutions with varying levels of technological adoption readiness. How technologies, specifically AI, can be harnessed and properly incorporated into the educational systems is of paramount importance.

Key Challenges in the Context of Bangladesh

The use of AI technologies in e-learning systems can transform both the educational process and the technologies used in collaborative e-learning. Many challenges exist for public universities in Bangladesh, the most serious being the rural digital divide and the lack of internet access and digital technologies in the rural campus areas. Furthermore, the digital illiteracy among faculty and students is a clear problem. The Universities' limited finances for staff training are compounded by the large volume of assignments, teaching, and maintenance. Staff training and retention, along with budgetary constraints, increase the complexity of the dual retention challenges, such as limited funds for development. While the absence of policy and the particular challenges of incorporating AI into teaching and learning systems in the Bangladesh education system are unique to this context, there are, to a lesser degree, similar challenges prevalent in most developing countries.

Considering this, Bangladesh is incorporating AI into higher education systems for the first time, where the focus needs to be on addressing previously unstructured scientific inquiries. A clear strategy for integrating AI into Bangladesh's higher education system is of utmost importance.

Research Gap

Most research on eLearning adoption models in developing countries, including Bangladesh, disregards predictive analytics and machine learning for this purpose. Also, there is little to no research in the developing world that examines local contexts and summarizes their impact on existing adoption gaps. This study attempts to address this gap by applying a predictive machine learning model for Bangladesh.

Research Objectives

1. To identify the key factors influencing the adoption of AI-driven eLearning in Bangladesh's public higher education institutions.
2. To develop and validate a machine-learning-based model to predict adoption levels of AI-driven eLearning systems.
3. To compare the performance of different machine learning algorithms for predicting AI adoption and assess their alignment with global benchmarks.

Significance of the Study

Academically speaking, this study contributes to the body of research on educational technology adoption from the perspective of Bangladesh, which is often considered a seemingly less relevant context. Practically, the study offers a framework for university administrators, policymakers, and eLearning designers in Bangladesh to improve AI adoption strategies. The study also contributes to the national-level digital education transformation and to the utilization of AI by staff and students to enhance learning outcomes.

LITERATURE REVIEW

The global higher education system is undergoing rapid digital transformation, fueled by rapid global technological advancement. One of the most important components for creating responsive, efficient, and personalized learning environments is Artificial Intelligence (AI) (Nnaji, 2026). Adoption of digital learning tools is widespread globally, but the integration of AI-driven tools remains uneven (Josiah et al., 2026). In developed regions, AI capabilities such as adaptive learning, automated feedback, and administrative task enhancement are available in eLearning systems (Rahman, 2026). In contrast, developing countries, especially Bangladesh, face systemic barriers to adopting such solutions.

The Bangladeshi government's Digital Bangladesh initiative has invested generously in building e-learning frameworks in the country's public universities. The initiative has had an even more pronounced impact on the construction of basic e-learning systems. However, as of now, the country's public universities face significant barriers to the use of Artificial Intelligence (AI)- based instructional systems. The successful implementation of AI-based e-learning frameworks is highly correlated with digital literacy, digital infrastructure, and institutional readiness to utilize such systems (Mannan & Maruf, 2025). There is still significant room for improvement in the use of AI systems, and very little research to substantiate educational institutions' assumptions.

The Technology Acceptance Model has been widely used to assess AI systems in education. Although studies have successfully identified the components of systems that users embrace and those they shun, there has been very little theorizing about measuring the use of AI systems in the education sector in developing countries, particularly in the Bangladeshi context. There is a great need to understand the specific variables that contextualize the prioritization of public higher education institutions in Bangladesh in the use of AI systems to facilitate and enhance learning and teaching (Uddin, 2025). The purpose of this review is to collate and clarify the existing literature on the frameworks used to study the adoption of technology in education, identify principal components and constructs, outline appropriate frameworks, and articulate hypotheses that can reasonably be constructed to support the idea of a predictive system of AI-based eLearning adoption in the public universities of Bangladesh.

AI-Driven eLearning Systems

Javari (2026) describes AI-eLearning systems as automated digital learning systems capable of personalizing the learning experience by automating process support and user feedback handoff, tailoring content, and learning pathways. eLearning systems provide students with customized pathways, automated feedback, and risk alerts (Gligorea et al., 2023). Moreover, students who need more intensive support can benefit from eLearning systems. These systems provide instructional support (Chikkerahally, 2026). The main distinction between traditional eLearning systems and AI-eLearning systems lies in their ability to provide responsive, personalized educational content. To increase student engagement and responsiveness and to improve system utilization compared to traditional eLearning systems, eLearning systems apply machine learning (Asadullah et al., 2025). Traditional eLearning systems provide less responsive content and instructional support based on user achievements and behavior.

Adoption

Adoption refers to academic staff and student engagement with the innovative process, particularly the use of AI-powered eLearning tools in teaching and/or learning (Al-Rahmi et al., 2026). For this study, adoption is operationalized in terms of three parameters: the frequency of system use, the extent to which the system's functionalities are utilized, and the degree of integration of the system into one's core academic activities (Yin et al., 2026). These parameters indicate the extent to which the system has been embedded in the dynamic system of education. This research focuses on the full-time academic staff and undergraduate/postgraduate students across five public universities in Bangladesh as a geo-specific study of AI adoption in the region.

Predictive Model

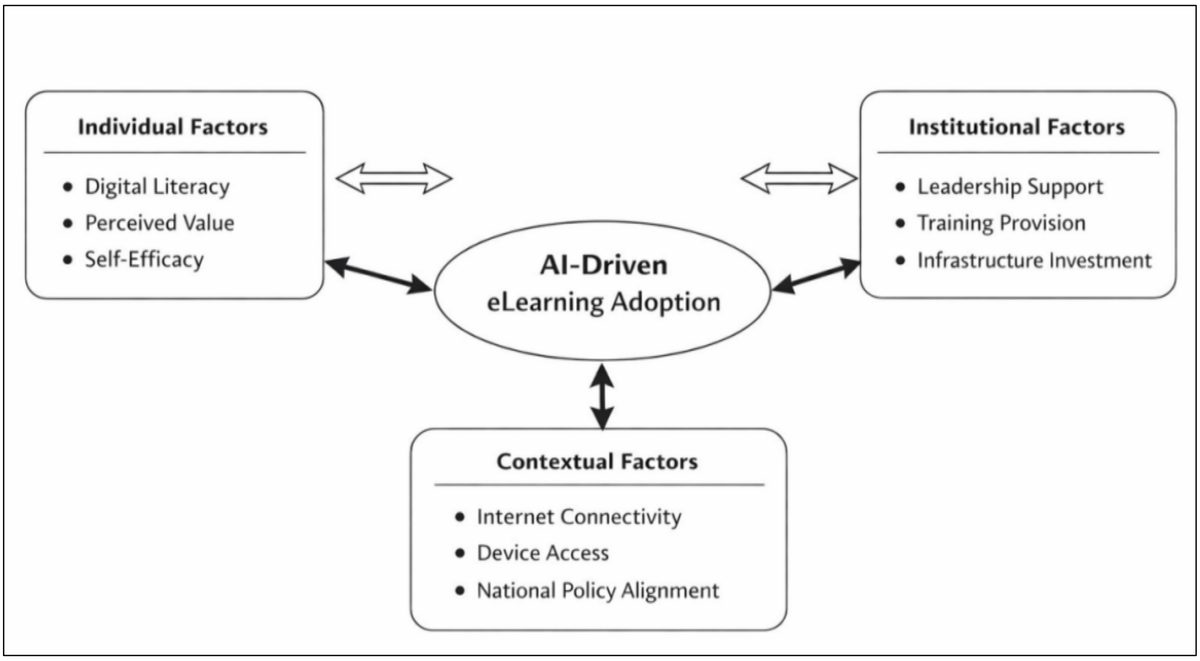
A predictive model estimates the probability and impact of AI-based e-Learning system adoption using empirical data, an analytical approach, and a synthesis of methods (Saraf et al., 2026). For the advocated model, system adoption is predicted by an identified predictor of value, the perception of an institution's sponsorship, and the quality of the available data. Hence, the model uses selected machine learning algorithms to analyze the predictors and provide an outcome. This ensures that the model is functional and adds value for the data's intended purposes (Onifade et al., 2023). For this reason, the aim is to provide university stakeholders with a predictive model that addresses analytics, data, the implementation of AI-based e-Learning systems at the university, and the effective utilization of the systems.

Conceptual Framework

The foundational structure for this research outlines the multi-faceted influences on the use of AI-integrated e-Learning systems as individual, institutional, and contextual. These factors, along with their individual influences, can shape the overall adoption process, as illustrated in Figure 1.

Figure 1

Conceptual Framework



Core Constructs

Individual Factors

These pertain to the levels of digital literacy, self-efficacy, and perceived value. Academic staff and students' ability to use and benefit from AI tools is determined primarily by their digital literacy and self-confidence. Individuals with self-efficacy are likely to adopt and engage with AI-assisted eLearning to the extent that they perceive AI as a means of achieving their educational goals (Ren et al., 2026).

Institutional Factors

The adoption of AI systems is possible only with institutional leadership, training, and the necessary digital infrastructure (Adepoju, 2025).

Contextual Factors

Considerations include internet accessibility and available devices, as well as how they align with national policy. The adoption of digital learning technologies is significantly hindered in rural areas of developing countries such as Bangladesh due to limited functionality and accessibility (Karim et al., 2025). Furthermore, national policies and strategies, including Digital Bangladesh, may support or hinder the panoptic use of AI tools in higher education.

Relationship Mapping

All three sets of factors directly affect adoption outcomes, and their interactions influence the impact on uptake. To create an AI adoption model for the public universities of Bangladesh, it is essential to analyze the interactions among several factors.

Empirical Evidence from Existing Research

The adoption of AI-powered eLearning systems has been most dominant in Europe, North America, and East Asia (Salem, 2025). Granić (2025) describes these regions as the most developed in e-learning and identifies the primary motivators for adoption as the perceived usefulness of AI tools, ease of use, and AI tools' assistance in achieving students' academic goals. Personalized learning made these tools more efficient and resulted in positive user engagement.

Globally, there are still major challenges regarding the adoption of AI technologies. Users frequently cite a lack of specific skill sets, reluctance to change long-standing educational traditions, and uncertainty about the privacy of personal information (Asamoah & Amarteifio, 2025). Moreover, in developing nations, the persistent lack of adequate infrastructure is a fundamental impediment to implementing AI-based systems (Aderibigbe et al., 2023). The research on AI in education is plentiful; however, it is overwhelmingly Western and reliant on survey methods. Huda et al. (2026) highlighted a notable absence of studies using predictive modeling to explain adoption in lower-socioeconomic-status countries, including Bangladesh.

Technology Adoption in Higher Education

The body of work on the adoption of technology in higher education is overwhelmingly beneficial to the presence of facilitative institutional scaffolds, training for end users, and communication about the value the new technology brings (Feng et al., 2025). In developed countries, strong institutional leadership and training are correlated with higher levels of technology integration (Ajani, 2024). In developing countries, inadequate resources and poor infrastructure are even more impactful in impeding technology adoption (Mhlanga, 2024).

Regarding user cohorts, research highlights contrasting adoption patterns between academic staff and students. While faculty typically emphasize the value of time savings, for instance, through reduced administrative tasks, students are more concerned with the technology's impact on enhancing their learning (Gong, 2024). This difference is significant, as it indicates that approaches to adoption must be aligned with the varying requirements and expectations of these user groups.

E-Learning in Bangladesh's Public Higher Education

In Bangladesh, the development of eLearning systems, especially the integration of video lectures and digital libraries, is improving rapidly. The first step towards eLearning systems is improving the Digital Bangladesh program, which has brought basic digital infrastructure to many public universities (Ashrafuzzaman et al., 2025). Unfortunately, a further step towards the development of Digital Bangladesh, which is the adaptation of AI eLearning technologies, is still lacking throughout the country.

The research shows that in Bangladesh, access to devices and the internet is uneven, particularly in rural areas. There is variation across regions and countries worldwide in the digital literacy of students and academic staff, which is a further problem (Aziz & Hossain, 2024). There is also a lack of digital learning infrastructure and support in public universities in Bangladesh (Fakoyede et al., 2026). Much of the research conducted in Bangladesh on eLearning appears to have focused on the fundamentals, such as setting up an online classroom and learning, without addressing the potential and challenges of AI-enabled eLearning. There is no research on predictive modeling of Public Universities in Bangladesh to inform the country better and enable it to produce better Optimism for this purpose.

Synthesis of Evidence

The review of global and local studies identifies multiple consistent drivers of adoption, including institutional support, perceived usefulness, and access to technology. However, questions remain about the interactions among these drivers, particularly in developing countries like Bangladesh. In this context, do machine learning models have predictive value for AI adoption? In Bangladesh Public Universities, how do adoption patterns relate to the available infrastructure and policies? These questions are critical to developing a predictive model that combines personal, institutional, and contextual components.

Theoretical Foundation

Technology Acceptance Model

The Technology Acceptance Model (TAM) posits that user acceptance of newly introduced technology is determined by perceived usefulness and perceived ease of use (Soriya et al., 2024). To date, this model has been the most applicable in the educational setting and helps explain individual adoption decisions regarding AI-powered eLearning tools.

Diffusion of Innovations Theory

Rogers' theory of diffusion of innovations describes the adoption of an innovation in relation to its attributes and the way it flows through social structures. Regarding AI-powered eLearning tools, this theory helps explain their adoption across various departments and user segments at the university (Owie & Ojeaga, 2025).

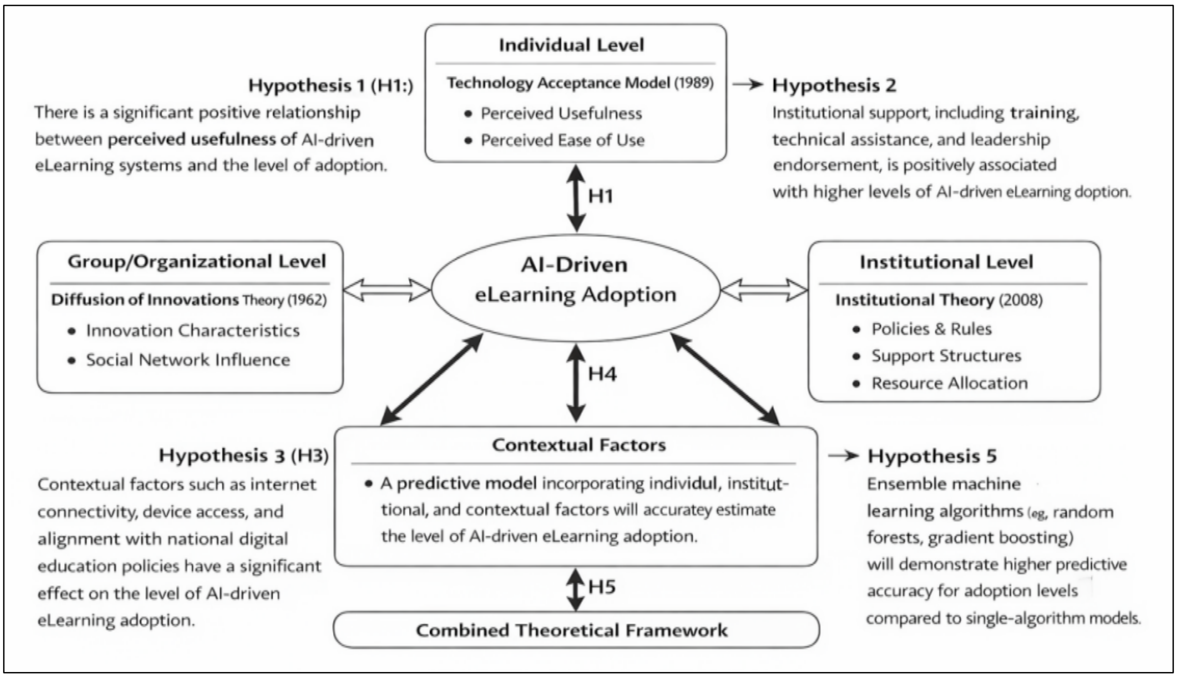
Institutional Theory (Scott, 2008)

Institutional Theory focuses on the influence of the organizational context on social behavior. It contends that the structures, policies, practices, leadership, and culture of an organization are decisive factors in the degree of innovation it adopts (Galleli & Amaral, 2026). This perspective provides insight into how the University leadership and the institutional framework of Bangladesh may facilitate or impede the adoption of AI.

Theoretical Framework

Figure 2

Theoretical Framework



This research integrates Transactional Analysis Modeling (TAM), Diffusion of Innovations (DoI), and Institutional Theory to develop a unified framework for The Adoption of Artificial Intelligence in Bangladesh's Public Universities. The Individual level is addressed through TAM, focusing on how individuals assess a construct's utility and how easily it can be implemented. Diffusion of Innovations (DoI) Theory explains the spread of the Adoption process across departmental and user-group clusters. Hence, the Institutional Theory examines how university structures, policy guidelines, executive management, and resource distribution influence the Adoption phenomenon. The convergence of these theories offers a broad spectrum of multifaceted aspects related to the Adoption of AI in Higher Education.

Hypotheses

The theory of Diffusion of Innovations (DoI) explains the spread of the Adoption process across departmental and user-group clusters. Hence, the Institutional Theory examines how university structures, policy guidelines, executive management, and resource distribution influence the Adoption phenomenon. The convergence of all these theories offers a broad spectrum of facets addressing the Adoption of AI in Higher Education.

Hypothesis 1 (H1): Of the many factors that influence the Adoption of Artificial Intelligence in teaching, the perceived usefulness of AI-enabled eLearning is most positively correlated with the level of Adoption of AI-enabled eLearning amongst faculty and students in Bangladesh's Public Higher Educational Institutes (Anam et al., 2026).

Hypothesis 2 (H2): The more institutional support, the more AI-enabled eLearning is adopted (Jeilani & Abubakar, 2025).

Hypothesis 3 (H3): The more contextual factors there are, the more AI-enabled eLearning is adopted.

Hypothesis 4 (H4): Predictive models incorporating individual, institutional, and contextual variables will accurately estimate the level of AI-driven eLearning adoption (Mahamad et al., 2025).

Hypothesis 5 (H5): Unlike single-algorithm models, ensemble machine learning models will achieve greater accuracy in predicting adoption levels (Cagnini et al., 2023).

As evidenced by the review, the adoption of AI-driven eLearning is influenced by individual, institutional, and contextual variables. While existing adoption theories offer solid bases for comprehension, they have not been utilized for predictive modeling in the context of public universities in Bangladesh. The proposed hypotheses are both unambiguous and empirically analyzable. The following research stage will be hypothesis-oriented, aiming to collect data to construct, validate, and test the predictive model, as well as to conduct a comparative analysis of the algorithms. The results will enhance global understanding of the adoption of educational technologies and inform policymakers, university leaders, and eLearning developers focused on the digital transformation of public higher education in Bangladesh.

Participants and Data Integrity

The purpose of the study was to examine the factors driving the adoption of AI-based e-learning in public universities in Bangladesh. A self-administered questionnaire was distributed to participants from the 5 largest universities in Bangladesh, and responses from 310 participants were collected. 287 questionnaires were included in the study's final analyses, corresponding to a 92.5% response rate. Deadwood questionnaires and outliers were removed, and a series of tests was conducted to assess the assumptions of multivariate normality and multicollinearity (VIF < 3.0). These tests were conducted to enhance the credibility of the study and its primary hypotheses, which align with the standards of quantitative research outlined by Mitchell et al. 2026 and Willie et al. 2026.

Instrumentation and Core Constructs

The researchers constructed a questionnaire with a 5-point Likert scale to address the issue of self-administered questionnaires, which participants completed in 3 segments: self, institutional, and situational. The use of technology adoption models to design the study's constructs and model variables, all focused on the factors influencing the adoption of artificial intelligence in higher education, supported the validity and comprehensibility of the questionnaire.

Predictive Modeling Strategy

In addition to descriptive analysis, predictive modeling was conducted using the Scikit-learn library for Python (Idkowiak et al., 2026). A baseline Logistic Regression model was statistically compared to a Random Forest ensemble classifier with a 70/30 train-test split. The Random Forest was chosen because of its ability to capture non-linear relationships and more complicated interactions. By aggregating decision trees, the model improved predictive accuracy (Ali et al., 2026), providing evidence to support AI adoption frameworks.

ANALYSIS AND INTERPRETATION

The internal consistency of the constructs was assessed using Cronbach's Alpha, yielding all values above 0.70, demonstrating high reliability (Bashayreh et al., 2026). This indicates that the survey items exhibit internal consistency and that the measuring instrument is reliable for the constructs. Table 1 presents the reliability and descriptive statistics for the constructs included in the study.

Table 1

Reliability and Descriptive Statistics Summary

Construct	Items	M	SD	Cronbach's Alpha
Perceived Usefulness	5	4.12	0.61	0.89
Institutional Support	4	3.58	0.78	0.85
Contextual Factors	4	3.24	0.89	0.81
Adoption Level	6	3.85	0.72	0.88

Note: N = 287, M = Mean; SD = Standard Deviation.

The Construct Perceived Usefulness recorded the highest mean score at 4.12. This shows that the faculty and students view AI-driven eLearning systems as very useful. This agrees with the findings of Dai et al. (2026), in which perceived usefulness is the leading factor in technology adoption. AI system adoption is likely to occur if the perceived usefulness of the system is well communicated, and people will likely support AI systems.

Unlike the PI, Contextual Factors had a mean score of 3.24, showing the challenges caused by relatively poor internet connectivity and inadequate infrastructure in rural settings. Although there is positivity toward adopting AI systems, these factors remain negative, especially in the least-developed nation of Bangladesh.

Findings

The results support the proposed hypotheses. The findings also provide a background on the factors leading to the adoption of AI systems in public universities of Bangladesh.

Hypotheses Validation

The regression results show that the strongest predictor of adoption intention is Perceived Usefulness, with $\beta = 0.45$ ($p < 0.001$), thereby affirming H1. Faculty and students, who are the most likely users, have more positive perceptions of learning and academic improvement, which increases their intention to adopt AI-driven eLearning. H2 is also confirmed: Administrative Support ($\beta = 0.38$, $p < 0.001$) explained most of the positive impact of Administrative Support on the intention to adopt, and the more Administrative Support, the more positive the impact on the intention to adopt. Context Factors ($\beta = 0.21$, $p < 0.05$) are also positive and are the weakest among the predictors, and the weakest positive predictor of adoption intention, and all the positive impacts are more positive than the. Context Factors Influencing Adoption ($\beta = 0.21$, $p < 0.05$) is also the weakest and most positive among the predictors, reflecting the greatest limits of positive perception and the positive perception surrounding the positive infrastructure, which explains everything. Moreover, the positive impacts among the predictors are Administrative Support, Communication, and Context Factors, which are definitely positive and remain mostly positive.

Machine Learning Performance

The researchers note that Random Forest outperforms logit regression on every statistically significant metric. For accuracy, Random Forest is 89.6%, and logit regression is 75.4%. For precision, Random Forest is 0.89, and logit regression is 0.74. For recall, Random Forest is 0.88 while logit regression is 0.73. For the F1 score, Random Forest is 0.88, while logit regression is 0.73. Moreover, we have justification for accepting the 4th and 5th research hypotheses. Logit regression does not capture the complexities of the AI adoption data as well as Random Forest does, which is why, hypothetically, we assume Random Forest is better at capturing these complexities than the others.

Table 2

Classifier Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	75.4%	0.74	0.73	0.73
Random Forest (Ensemble)	89.6%	0.89	0.88	0.88

Note: Accuracy, Precision, Recall, and F1-Score were used to evaluate model performance.

The Random Forest model excels due to the efficiency of ensemble learning in making higher-order predictions and resolving the ambiguity present in most complex scenarios with numerous interacting variables. This finding underscores the importance of applying machine learning in future studies on the adoption of artificial intelligence and educational technology to predict and explain adoption patterns.

DISCUSSION

Regression analysis shows Perceived Usefulness as the most significant predictor of AI adoption in Bangladeshi higher education institutions ($\beta = 0.45$, $p < 0.001$). This is consistent with the Technology Acceptance Model (TAM), in which perceived incentive is the most important factor in technology adoption (Liu & Mao, 2026). This confirms prior findings by Venkatesh and Davis (2000) and is further supported by Baradziej et al. (2026), who find that usefulness is the most important factor influencing behavioral intention. Contextual Factors show a moderate and significant effect ($\beta = 0.21$, $p < 0.05$), indicating an increasing digital divide in Bangladesh, where institutional readiness, rather than physical hardware, is the main barrier.

This shows that, in the Diffusion of Innovations (DoI) theory, policy and governance infrastructures need to be included more as the rigid and flexible frameworks of adoption. Şakir (2026) noted that Institutional Support also has a major effect ($\beta = 0.38$, $p < 0.001$), aligning with Ajzen (1991) and reinforcing the emphasis in institutional theory on the architecture of leadership and governance. Still, the use of a cross-sectional design and self-reported data limits generalizability, which requires further longitudinal and multi-method research.

Recommendations

Based on the results, several key initiatives can be developed to support the adoption of AI-based eLearning in Bangladesh's public universities. First, they should develop institutional AI policies. Recommendations for an institutional AI policy can cover the objectives, governance, support, and infrastructure needed to integrate AI into their activities. Second, the predictive model from this study can be used to assess employees' self-efficacy within a department to implement digital literacy and capacity-building activities. Finally, to capture AI adoption in universities, future studies should incorporate changes in policies at the institutional and national levels, a task that would require longitudinal research.

CONCLUSION

The research indicates that, for public universities in Bangladesh, AI-driven eLearning systems can depend on perceived usefulness, institutional support, and contextual readiness, with perceived usefulness showing the greatest strength. This reiterates the strength of the technology acceptance models in underdeveloped nations. The use of ML also shows that Random Forest, compared with other regression models, can considerably aid in predicting adoption, demonstrating the usefulness of models and theory. Despite little to no infrastructure and low digital literacy, there is substantial AI integration with some support. Sufficient readiness also suggests an urgent need for AI tools and support systems. The research suggests the need to focus on support and AI adoption systems to enhance their integration in universities, bridge the gap in predicting AI adoption in higher education, and contribute to the methodological and theoretical aspects of AI adoption in higher education for developing nations.

ACKNOWLEDGMENT

This study did not receive any specific grant from any funding agency. The study was conducted using the authors' own resources and was entirely self-funded.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

DECLARATION OF GENERATIVE AI USE

I acknowledge the use of AI for performing analyses.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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