Enhancing e-Learning with AI and Blockchain: A Predictive Analysis of Acceptance Factors and Academic Performance

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The research paper explores the key issues that determine the acceptance of eLearning tools by students and their effect on academic performance. Although the Technology Acceptance Model (TAM) has been used as the main model to describe adoption behavior in the past, little focus has been on the relationship between acceptance and performance outcomes. To fill this gap, we suggest a combined IS-TAM framework and confirm it using two datasets collected from higher education institutions (N = XXX). The results of Structural Equation Modeling (SEM) show that Perceived Ease of Use has $\alpha = 1.00$ ($p < 0.05$), Perceived Usefulness ($\alpha = 0.8$, $p < 0.01$), and System Quality ($\alpha = 0.87$, $p < 0.01$). Moreover, the accuracy of the Machine Learning model was 0.79, indicating good predictive performance based on factors related to acceptance. The findings indicate that acceptance modeling coupled with predictive analytics is a more holistic way of understanding eLearning effectiveness. The study is valuable in that it bridges a gap between the behavioral and performance perspectives, which can be used in practice to enhance the design and student achievement of eLearning systems.

Keywords: E-Learning, Human-Computer Interaction, Performance Impact

Introduction:

Innovation and recent developments in education systems around the world have positioned technology as a backbone, resulting in the emergence of e-Learning., a novel mode of knowledge acquisition [1]. The methodology of e-Learning aims to deliver dynamic education using modern technological tools [2]. Since its inception, e-Learning has transformed traditional education by allowing access to productive resources, promoting collaborative learning, and fostering an awareness of the Technology Acceptance Model (TAM)-based education [3]. Unleashing novel and progressive mechanisms for interactive communication, independent knowledge acquisition, and e-training for the corporate sector are other distinctive goals of e-Learning [4]. Bridging communication gaps, enhancing student attention, and increasing frequent tool-based contact between teachers and students are impactful features of e-Learning [5].

The spread of COVID-19 has had adverse effects on the social, commercial, political, and educational dynamics across the globe. In this state of crisis, transforming the educational system through e-Learning is undoubtedly a positive ray of hope [6]. Unlike conventional teaching methods, e-Learning presents certain limitations and challenges. Below are key areas that need to be addressed to make e-Learning a success during these catastrophic circumstances:

Teachers and students should be skilled and competent enough to make proper use of e-Learning tools.

E-Learning Learning Management Systems (LMS) should be efficient, secure, reliable, and technically sound to provide the required user interface and user experience.

E-Learning-based education should offer a virtual classroom-like environment to replace and facilitate face-to-face (F2F) education.

Governments should approve uniform policies and infrastructure to encourage e-Learning, considering social distancing as the need of the hour.

There have been notable efforts in the past to acknowledge that e-Learning primarily facilitates information, communication, and access to resources among its users [7]. Nevertheless, e-Learning is increasingly in demand for its exclusive capabilities to handle time and cost-effectiveness [8]. This also paves the way for researchers to explore potential factors that can affect student acceptance and their impact on performance [9].

Despite several attempts to formalize e-Learning using standard theories like the Technology Acceptance Model (TAM), Innovation Diffusion Theory, Unified Theory of Acceptance and Use of Technology (UTAUT), and the DeLone McLean model [10], these models have primarily focused either on user behavior for e-Learning adoption or on predicting usability levels. Given the severity of the current situation and the need to meet educational objectives, it is essential to frame e-Learning within an integrated reference of the Technology Acceptance Model (TAM) and Information Systems (IS). This research takes a step forward in devising an integrated IS-TAM model with the following major contributions: We present a detailed study of recent research in terms of evaluation mechanisms and combined IS-TAM approaches. This paper focuses on developing a comparative and analytical assessment of students' perceptions from three different academic environments in the USA and Pakistan. Moreover, this research attempts to bridge the gap between different factors of IS and TAM models, such as Perceived Usability, Perceived Ease of Use, Usability, Overall Quality, and their influence on User Satisfaction, Intent to Use, and ultimately the acceptance of e-Learning tools and their impact on performance.

In concise terms, grades are considered a benchmark for evaluating performance in educational systems. Predicting student performance in any mode of education is crucial, as it is tied to their academic future. Recent research has focused on enhancing student learning through educational data mining (EDM) and psychometric analysis [11]. However, predicting performance remains a challenging task, as it involves many machine learning methodologies that often encounter issues with forecast precision. As explained earlier, COVID-19 has brought a paradigm shift in the entire academic system, including online assessment procedures using e-Learning tools. Extraordinary economic and educational circumstances have driven policymakers to opt for optimized, student-friendly, and technically reliable e-Learning tools. As a result, this would create a better environment for delivering lectures, improving the quality of communication in online classrooms, and allowing students to adapt to new assessment mechanisms. Embedding a quality assessment subsystem within e-Learning tools can help underperforming students, especially those without an IT background, and guide deserving students in the right direction. Undoubtedly, e-Learning tools hold immense potential to influence student performance by allowing them to continuously monitor their progress.

The integration of Artificial Intelligence (AI) in eLearning systems has further transformed the learning environment with adaptive, personalized, and effective learning experiences that cater to particular needs. AI technologies have the potential to transform education systems through personalized support, test automation, and optimizing teaching and learning effectiveness. Computer-based applications, such as intelligent tutoring systems, automated testing systems, and learning platforms, aim to improve instructional quality by customizing content presentation in accordance with learners' requirements and providing immediate feedback, facilitating self-learning.

In this research, we aim to align student performance with the acceptance of online tools, identifying factors that enhance learning efficiency and improve performance. Therefore, providing insights into student performance and its impact is a key contribution of our research. Our predictive analysis will help students develop a better understanding of their performance in e-Learning-based education. Additionally, educational institutions can leverage our prediction-based research for capacity building, value-based education, and course outcome-based student performance evaluation.

In this study, we briefly outline our research methodology, which includes a survey from three higher education institutions and the application of a state-of-the-art hybrid technique combining Structural Equation Modeling (SEM) and Machine Learning (ML) to develop a predictive assessment. Our research model is illustrative and deliberative enough to establish connections between determinant factors and performance outcomes in e-Learning. The obtained results from several analyses using SEM and ANN indicate that the factors studied are quite effective in influencing performance outcomes.

We opted for the Technology Acceptance Model (TAM) over other models because it is a widely recognized framework with a strong track record in technology acceptance research. TAM's constructs, such as Perceived Ease of Use and Perceived Usefulness, align closely with the factors influencing e-Learning tool acceptance in the educational context. Its simplicity and previous utilization in similar research make it a practical choice. Moreover, TAM's actionable insights offer valuable recommendations for improving e-Learning tool design and implementation, a critical consideration in the current era of increased online education due to the COVID-19 pandemic.

The following are key research objectives for this study:

To explore the connection between acceptance-related aspects and student academic achievements, it is necessary to go beyond the conventional adoption-oriented studies.

To create an integrated IS-TAM analytical model that is capable of representing both behavioral (acceptance) and outcome-based (performance) aspects of eLearning.

To empirically verify the framework proposed based on real-life datasets that are gathered in various academic settings (e.g., the USA and Pakistan).

To use Structural Equation Modeling (SEM) to examine causal relationships between acceptance factors, including perceived ease of use, perceived usefulness, and quality of the system.

To use machine learning methods to predict student performance using acceptance factors identified, and to make the model more practically applicable.

In section 2, a brief literature review and a summary of past research work are presented. Section 3 outlines the research model of this study. In Section 4 Hypothesis of the study are elaborated for validation purposes. Section 5 provides an understanding of the evaluation mechanism set for this study. In Section 6, results and data are analyzed, interpreted, and illustrated with pros and cons. Section 6 concludes the study, mentioning key implications, inferences, and practical contexts.

Literature Review:

Several studies in the past have mainly focused on challenges for E-learning acceptance, especially in developing countries [12][13][14]. Generally, there were several factors, approaches, and objectives for e-learning acceptance taken into consideration for conducting a scientific overview and analysis. Further, our research review is based on the literature of different categories of techniques, factors, and objectives, summarized in separate tables.

Table 1 shows the literature review of the identification of factors that affect students' acceptability towards e-Learning. This literature explains the TAM models and their adoption in various research studies of student acceptability using different Quantitative methods and techniques like SEM, Regression analysis, etc. In our study, we expand factors (termed as high consensus factors in our paper) studied in this literature to e-Learning tool (e-Learning communication medium like Zoom, Google Meet, Blackboard, etc) acceptability and performance. Further, Table 2 shows the literature of the next step of our research, which is based on the academic performance impact using e-Learning tools (Zoom, Meet, Blackboard, etc.). We included the most relevant papers that used different statistical methods to assess student performance. Similarly, in Table 3, we focus on recent research studies that exclusively focus on the hybrid SEM-AI approach. In our study, we extended this literature as our objective methodology to predict the students' academic performance.

Based on this review, we believe that there is a need of developing novel research model that can be effective in unorthodox situation COVID-19 pandemic. Most importantly, this research study is aimed at facilitating educational institutes, academic policy makers, and students to have a credible assessment of their grading and performance.

Although there is a wealth of literature on the adoption of eLearning, the current research has largely been based on the Technology Acceptance Model (TAM) to understand the behavior of users, but with a greater emphasis on intention to use and less on actual learning results. The majority of the previous research considers the concepts of acceptance and performance as two distinct variables, ignoring the important connection between the perception of eLearning systems by students and their academic success. Moreover, little has been done to combine TAM with Information Systems (IS) success factors to offer a comprehensive view of system effectiveness. Methodologically, the conventional methods mainly rely on single methods of analysis, including regression or Structural Equation Modeling (SEM), without taking advantage of the predictive power of machine learning. This introduces a hole in the explanatory richness and predictive power. Hence, it is evident that there is a necessity for a unified framework that not only analyzes the determinants of acceptance but also quantitatively correlates them with student performance through a hybrid method of analysis. This research fills this gap by integrating ISTAM constructs with SEM and machine learning to offer both causal and predictive assessment of eLearning effectiveness.

Research Model:

Owing to increased operational and maintenance costs, the multi-faceted nature and interrelated complications have brought e-Learning education under discussion in many educational institutions across the world. There have been several attempts to develop effective models and tools that may pose the best-fit attributes of educational information systems in pandemic situations when traffic is so high on eLearning tools. [15]. Primarily, there were six basic factors identified as attributes of information systems, i.e., system quality, information quality, system use, user satisfaction, individual impact, and organisational impact. Evolution in information systems was sought to be always inevitable to meet ever changing technological requirement as any software system like in e-Learning communication tools. Later on, in 2003, the prototype of information systems was updated with features like intention to use and service quality [16].

Table 1. Literature review of factors identification of Student acceptability towards eLearning

Ref	Identified Factors	Approach	Summary
[19]	Innovation, knowledge sharing, perceived usefulness, quality, trust	Structural Equation Modeling (SEM)	This study validated an advanced technology adoption model based on two intrinsic motivational traits, living standards and social behaviour, for countries with low GDP.
[20]	Learning behaviour of students towards technology in specific courses and their teaching preferences	Structural Equation Modeling (SEM)	The proposed study aims to figure out characteristics that affect students' perception of e-learning in a mixed academic environment. The study concluded empirical analysis that e-learning is positively perceived as useful in a given scenario.
[21]	system quality, instructor quality, service quality, course quality	Regression analysis	This research focuses on factors that have an influence on the satisfaction level of learners. This research also framed their research upon the updated DeLone and McLean (DM) model.
[22]	innovation, quality, trust, knowledge sharing	Structural Equation Modeling (SEM)	This article studies factors and approaches for college students involved in e-Learning-based education. Onwards, they also proposed a model for knowledge exchange through reliable technology tools, ensuring acceptance of e-learning.
[23]	Efficacy of computer usage, quality of information system, and access to learning tools.	Structural Equation Modeling (SEM)	This study was conducted to discover additional characteristics that may influence e-learning acceptability. A literature review was conducted. Furthermore, major findings included the positive impact of an enhanced information system and the perceived usefulness of an e-learning system.

Over the years, IT researchers have made possible the extension, integration, and incorporation of various aspects into the conventional D&M model for education. [17] mapped technical system quality, service quality, and user satisfaction towards system loyalty as the first research-based effort towards e-Learning. On the other hand, [18] introduced user experiences, perceptions, and their behaviour as integral components of the Technology Acceptance Model (TAM). All these models were attempts to bring innovation for developing high-quality e-Learning tools to ensure their compatibility and acceptability in different academic environments and particular resource settings. As explained earlier, re-orientation and re-alignment of the educational system in emergency conditions has produced a research urge for synergy of TAM and D&M models. Therefore, we have proposed a model that potentially depicts integrated settings of TAM and D&M, while considering high consensus factors.

Table 2. Literature review of the impact of eLearning tools on student academic performance

Ref	Approach	Summary
[24]	Statistical Analysis	This study examined and found that there were statistically significant differences in students' academic performance when implementing e-learning strategies in catastrophic circumstances. The results of the research show that implementing e-learning strategies in universities is essential to improving students' academic performance. It also clarifies that specific characteristics of certain courses must be considered (for example, Arabic language and social studies.
[25]	Structural Equation Modeling (SEM)	This study put forward findings related to the impact of e-learning on the academic learning Level of students studying in college. Researchers conducted research using quantitative research methods. Analyze data and use frequency and frequency statistics techniques, percentage. Research shows that e-learning provides students with time flexibility. It motivates students to do their own work without the help of others. Research has concluded that e-learning provides students with flexibility in learning time and motivates them to do so. Work without the help of others.
[26]	Literature review through machine learning techniques	In this study, nearly 70 papers were analyzed, demonstrating various modern techniques that are commonly used to predict student performance. These techniques and methods included artificial neural networks and recommendation systems segregation.
[19]	T-test, one-way ANOVA, Pearson correlation coefficient, and simple linear regression analysis.	Investigation of e-learning correlation is the main aim of this study. The academic performance of online students depends on the course interests. Variables for early school leavers and dropout rates are considered. In this study, the participation time level of open and distance learners was considered. Compare their academic achievements. Found a significant improvement in academic performance
[27]	linear Pearson correlation tests, regression analysis.	discusses multiple linear regression analysis and shows that there is a relationship between the two Link grades and total grades for online assignments, the student's course level. The study investigates the other two Independent sample t-tests to compare results.

This section intends to develop a theoretical model consisting of factors explaining and predicting student tool acceptance and their impact on academic performance in a higher education e-Learning environment.

Figure 1 depicts that human behaviour in e-Learning can be modeled in terms of high consensus factors, like Perceived Ease of Use (PEOU), Perceived Usability (PU), Usability and Overall Quality (QS). Furthermore, these factors are incorporated to form a relationship with the baseline TAM model consisting of User Satisfaction (US), Actual Use (AU), and Intention to Use. It hypothesizes that the academic performance impacts of students can be determined by the students' acceptance factors of e-learning.

Table 3. Literature review of the impact of eLearning tools on student academic performance

Ref	Approach	Summary
[28]	Hybrid SEM-AI	In this study, modern machine learning techniques were utilized to predict social addiction towards the problem statement. It was concluded that methodology can be useful for determining the priority of management measures.
[29]	Hybrid SEM-AI	This research forms the basis for our approach implemented in a broad perspective. It deployed a hybrid technique, structural equation modelling (SEM) and artificial neural network (ANN). This was a deterministic approach to obtain factors affecting systems developed using Enterprise Resource Planning (ERP). This research further tested the hypothesis of the technology acceptance model (TAM) as an extended work in terms of concept and methodology.
[30]	Hybrid SEM-AI	The purpose of this article is to predict the driving factors for learning social media, particularly Facebook. The existing data on the subject lacks analytical credibility. Therefore, structural equation modeling shows that sharing of knowledge, resources, and opinions is an influential determinant during higher education. These mainly authenticated factors are perceived usefulness, perceived enjoyment, connecting with the community, and participating in the virtual social world.
[31]	Hybrid SEM-AI	This study examined factors that were the research intention and adoption strategy to use the repositories of the institution. In particular, attitude, effort expectancy, and performance expectancy were determinant variables of the study. This study uses a hybrid technique of SEM-AI to put forward a predictive comparison of factors.
[32]	Hybrid SEM-AI	This paper presents a qualitative and quantitative assessment of students' study management. This article further determines motivation to adopt mobile-based learning. Hybrid techniques of SEM and ANN are employed to test the proposed research model and report the expectancy of performance and the expectancy of effort.

Development of Hypotheses:

The primary goal of the study was to determine student acceptability of the tools used in e-learning and identify the variables that increase the motivation of undergraduate students in the learning process. To achieve this, several research hypotheses were tested, based on the research model examined in this paper, to determine which hypotheses should be accepted and which should be rejected.

Perceived Ease of Use:

Researchers worldwide have recommended the Technology Acceptance Model (TAM) as a standard for measuring students' acceptance of e-learning tools. Consequently, studies related to TAM have proposed several key variables, such as Perceived Ease of Use (PEOU), where an individual believes that using a specific system will be easy [33]. Perceived Ease of Use (PEOU) has been shown to have a strong and positive impact on the intention to use the system [34]. Therefore, the argument that greater perceived ease of use leads to a stronger positive influence on the intent to use holds. PEOU is also considered to have a significant effect on various other e-learning factors, such as satisfaction and perceived usefulness [34]. This insight led us to develop hypotheses related to PEOU in our research context as follows: H1: Perceived Ease of Use will have a direct positive influence on user satisfaction with using e-learning tools. H2: Perceived Ease of Use will have a direct positive influence on the actual use of e-learning tools. H3: Perceived Ease of Use will have a direct positive influence on user intention to use e-learning tools.

Perceived Usefulness:

The decision to accept or reject information technology is influenced by several variables. However, from a usage perspective, Perceived Usefulness (PU) is considered a key determinant in TAM. Perceived Usefulness is defined as "the degree to which a person believes that using a particular system would enhance their job performance." Several studies have found that Perceived Usefulness affects user satisfaction with various information systems, including e-learning systems [35][36]. Research has also concluded that PU has a direct impact on both the system and its users. Furthermore, PU has been shown to significantly and positively influence online academic models [37]. Based on this theoretical foundation, the following hypotheses will be tested in our study.

H4: Perceived Usefulness will have a direct positive influence on user satisfaction with using e-learning tools.

H5: Perceived Usefulness will have a direct positive influence on the actual use of e-learning tools.

H6: Perceived Usefulness will have a direct positive influence on user intention to use e-Learning tools .

Usability:

Usability improves a student's acceptance of the value of using the e-Learning tool discuss the ISO 9241 approach regarded usability as "a property of the overall system: it is the quality of use in a context". Thus, the hypothesis below:

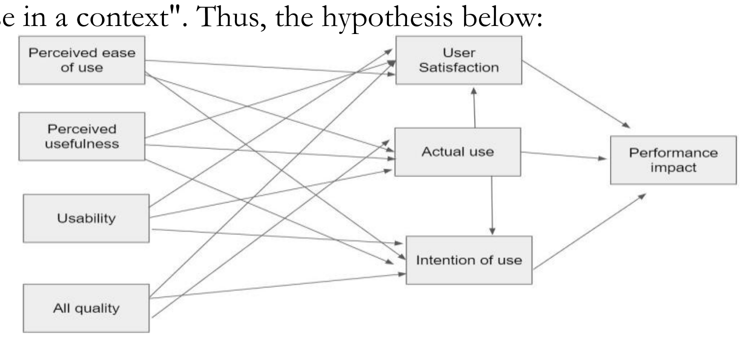


Figure 1. Proposed Research Model

H7: Usability will have a direct positive influence on user satisfaction with the use of the e-Learning tool.

H8: Usability will have a direct positive influence on the Actual use of the e-learning tool.

H9: Usability will have a direct positive influence on the user's intention to use the e-learning tool.

Overall Quality:

Quality is considered a crucial and fundamental component of any Information System (IS). Researchers have further categorized quality into Educational Quality, Service Quality, and Technical Quality. Educational Quality refers to the extent to which a learning environment is conducive and effective [38]. It can influence individual satisfaction with the academic process and its smooth operation. A well-developed Information System is expected to deliver the desired and perceived services to its users, which constitutes overall Service Quality. Although Service Quality is often perceived as an independent variable, it remains a significant dimension contributing to the overall quality of an Information System [39]. The importance of Service Quality is closely linked to the satisfaction of students and users of IS in the e-learning context [40]. Technical Quality is defined in terms of accuracy, efficiency, architectural efficacy, operational reliability, and functional correctness of any Information System. The IS success model is primarily based on the technical characteristics of the system [41]. Technical Quality is assumed to have a significantly positive impact on all parameters of information in the e-learning context [42].

Based on these theoretical foundations, the overall quality of the system is expected to positively impact student acceptability. Particularly, the multi-dimensional quality attributes of the information system are anticipated to influence student acceptability. Therefore, it can be inferred that if the system is easy to use, has high course quality, and focuses on service quality, students are likely to use it more frequently, and this increased use will positively impact their satisfaction. The hypotheses related to this factor are listed below:

H10: Quality will have a direct positive influence on user satisfaction with using e-learning tools.

H11: Quality will have a direct positive influence on the actual use of e-learning tools. H12: Quality will have a direct positive influence on user intention to use e-learning tools. User Satisfaction:

The concept of satisfaction has been discussed and measured by many researchers over the years and in many places [43][44]. However, student satisfaction is determined learning and experience. More recently, student satisfaction can be defined as the performance of conditions related to the experience and perceived success of academic services in eLearning [44]. Student satisfaction is an important indicator of the quality of student learning. Therefore, it is important to measure student satisfaction with different learning and teaching experiences as students interact with teachers and peers using new technologies of eLearning [45]. Student satisfaction in any situation is an idea or perspective of various factors that influence a situation [46]. So, the hypotheses of this factor are listed as follows:

H13: User Satisfaction is a factor of students' tool acceptability that would predict the performance impact.

Actual Use:

Providing the success of e-learning requires users to use it [46]. Therefore, the AU pushed is a straight explanation of student acceptance of available literature [46], [47]. Therefore, it is important to seek student satisfaction with different technologies used in learning and teaching because new technologies have changed the way students interact with teachers and classmates [47]. Therefore, we focus on proposing the following hypothesis: H14: Actual use will have a direct positive influence on the user satisfaction with the e-learning tool.

H15: Actual use is a factor of students' tool acceptability that would predict the performance impact.

H16: Actual use will have a direct positive influence on intention to use the e-learning tool.

Intention To Use:

The presence of Intentions of Use (ITU) in the TAM is one of the main differences. The ITU is a direct harbinger of the intended use and gives an indication of the willingness of a person to carry out a certain behavior. [48] PU and PEOU influence a person's intention to use the technology in TAM to control the usage behavior [49]. There has been much support in the literature for the relationship between ITU and usage behavior in general. [50]. This has recently been extended to the e-learning context. Therefore, we propose the following hypothesis:

H17: Intention to use is a factor of students' tool acceptability that would predict the performance impact.

Evaluation Mechanism:

Predicting student performance mainly focused on examining the extent of e-Learning tool acceptability. The flow diagram of our experimental and research methodology is pictured in Figure 2.

The flow diagram in Figure 2 depicts a research strategy consisting of a survey procedure, followed by the creation of a data set, data normalization, and then an evaluation mechanism using a hybrid approach (SEM-AI). The flow of data in this study is based on a structured pipeline that incorporates explanatory and predictive analysis to determine the effectiveness of eLearning. First, the researcher gathers the data of students in various academic settings using structured questionnaires that measure the main constructs of perceived ease of use, perceived usefulness, system quality, user satisfaction, and intention to use. Structural Equation Modeling (SEM) is used to analyze the data after preprocessing and validation to determine the causal relationship between these factors and quantify the impact of each factor on eLearning acceptance. The key variables found using SEM are then used as input variables in the second step, where machine learning models are used to forecast student academic performance. It is a two-step hybrid model that allows the research to not only describe the underlying behavioral determinants of eLearning adoption but also determine their influence on performance outcomes using predictive modeling. The integrated approach, therefore, offers a holistic perspective of the acceptance and effectiveness of eLearning systems that can be used to offer valuable insights on how to enhance educational practices and system design.

Research Participant:

As a general perception, the reliability of a survey can be questionable if conducted within a limited domain. To enhance the validity of the survey, we distributed the questionnaire across three universities: two in Pakistan and one in the United States. Our target participants were students enrolled in formal undergraduate and graduate-level education. Due to COVID-19, the entire educational process was conducted online. Therefore, it can be reasonably inferred that the sample collected represents a credible population. The sample size, consisting of nearly 2,000 students from three different academic environments, is sufficient to fit our research model.

Survey Instrument:

We designed our survey instrument as a formal questionnaire considering: 1. Students are more convenient and aware enough with questionnaire-based surveys; 2. The survey can be transformed into spreadsheet-based dataset questions as a variable; 3. The survey consists of two parts; the first part contains demographic variables related to the study, and the second part contains information regarding several factors, perceived usability, perceived ease of use, and overall quality of using the online e-Learning tool.

Furthermore, this questionnaire was verified and updated incrementally after obtaining recommendations from 3 different academicians.

Data Collection:

Data collection with considerable integrity by participants is the primary step towards the validity of this research. The survey instrument described was developed using a checklist of questions, which are further referred to as input and output variables. Table 4 summarizes the checklists.

SEM-Machine Learning Modeling:

A two-stage hybrid approach combining Structural Equation Modeling (SEM) and ML algorithm is employed to determine the relationships among independent and dependent variables. SEM is commonly used to analyze linear relationships among variables, while ANN is highly effective for evaluating the effects of independent variables on dependent or decision variables. Specifically, SEM conducts hypothesis testing, whereas ANN performs predictive modeling.

In this section, we present the research findings and results, which include a statistical analysis of the entire research model. SEM was applied to our dataset using Smart-PLS 3 software, an advanced tool that offers unique and valid results compared to SPSS and SPSS AMOS. As mentioned earlier, the results obtained from SEM provide a quantitative description of the dataset, elaborating on the impact of several hypotheses. This approach provides a naturalistic illustration by offering a clear understanding and interpretation of social phenomena. In subjective research contexts, SEM-based methodology helps model psychological parameters such as user satisfaction, actual use, and intention to use based on defined criteria. The techniques include survey-based questionnaires.

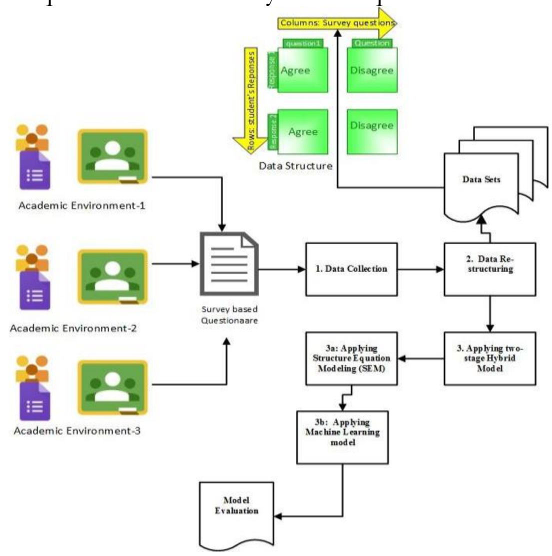


Figure 2. Proposed Research Model

From a technical perspective, Smart-PLS 3 was chosen for its ease of use and convenience. On the other hand, ANN, derived from neural networks in the human brain, processes sensory data through methods such as machine recognition, labeling, or clustering. ANN uses pattern-matching techniques and vectors, which represent real-world visual, pictorial, textual, and spatial data. Neural networks employ learning algorithms to tune data from input to output. The ANN method helps technical programs operate effectively and efficiently by applying different parameter settings for hidden layers and conducting reinforced training and testing of datasets to predict outcomes based on independent and dependent variables.

Data Analysis and Results:

In this section, a detailed illustration, analysis, and interpretation of data, methods, and results of the application using two distinct techniques.

Methodology:

Table 4. Checklist question items along with their abbreviated symbols

Factors identified	Corresponding questions
E-learning Acceptability	
EA1	I prefer to study online.
EA2	Awareness of E-learning platforms (Zoom, Meet, etc.) is essential.
EA3	E-Learning takes time to prove its trustworthiness.
Perceived Ease of Use	
PEOU1	Using and practicing the e-learning system tool is comfortable.
PEOU2	Finding the E-learning tool keys was easy.
PEOU3	While interacting with the e-learning system tool, every feature is understandable to use.
PEOU4	I have become skillful at using the e-learning system tool so easily.
PEOU5	I did not need any kind of training before using the e-learning system tool.
Perceived Usefulness	
PU1	Complete learning tasks faster,
PU2	My learning capability has improved.
PU3	It is easier for me to learn the course content.
PU4	I can easily interact with the instructor while using the tool.
PU5	Enhance my effectiveness in learning.
Usability	
US1	I am fully satisfied with this system usage.
US2	I was able to use this tool to complete tasks and scenarios.
US3	I felt comfortable using this tool.
US4	I think I was able to increase my productivity immediately with this tool.
US5	The tool displayed an error message that clearly tells me how to fix the problem.
Quality	
QU1	e-learning tools are user-friendly.
QU2	The instructor responds to learners via the e-learning system promptly.
QU3	Instructors regularly update their e-learning system lecture notes.
QU4	Course content is in a variety of forms – audio, video, texts, etc.
Intent to Use, User Satisfaction, Actual Use	
SAT1	The e-Learning system tool is fully responsive to your questions.
IU	The e-Learning system tool is frequently used.
AU	I prefer online education to F2F learning.

Evaluating and testing hypotheses requires a critical approach. In this study, we employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 3

[51]. PLS-SEM is recognized as an efficient technique for concurrently examining measurement and formulating structural models with improved precision of results [52][23][53]. ANN extends the results obtained from SEM by refining the training and testing of datasets to develop predictive models and perform sensitivity analysis.

Normalizing the questionnaire data, which was ranked on a Likert scale from 1 to 5, was essential. In social science research literature, linear procedures for data normalization are often used to bring data into a reasonable and computationally manageable form. In predictive analytics, N-fold and N-times cross-validation procedures are utilized to 1https://www.smartpls.com/ obtain unbiased results. The ANN model separated the data into training and testing portions, using three hidden layers and setting the linear output to false to ensure maximum credibility of results.

We utilized R2 for modeling student performance, using Accuracy, F-Measure, and Root Mean Square Error (RMSE) as evaluation metrics. R is an open-source software for statistical computing with a comprehensive library of machine learning algorithms. To facilitate replication of results, we have made our data, questionnaire, and experimental code publicly available on our repository.

Descriptive Statistics:

The demographics of the respondents are summarized in Table 5. Out of the total 260 responses, 200 were males (68%), and 60 were females (32%). The respondents were evenly distributed across age brackets, with 130 individuals aged 18 to 25 years (50%) and 130 individuals aged 25 to 30 years (50%). The study also assessed the educational levels of the respondents. The majority of respondents held an undergraduate degree, totaling 180 individuals (70.37%), while 80 respondents had a Master's degree (30.53%).

2https://www.r-project.org/

3https://github.com/Analyzer2210cau/Student-s-Tool-Acceptability-ANN-Approach)

Measurement Model Assessment:

In this section, we performed SEM-based calculations of the measurement model to ensure the quality criteria of the factors under investigation. This model includes several measures such as Reliability and Validity, Discriminant and Convergent Validity, Loadings and Cross-Loadings, and the Heterotrait-Monotrait Ratio (HTMT). Each of these measures has specific benchmark and cutoff values that reflect the proficiency of the analyzed variables.

Reliability and Validity:

In our study, reliability pertains to the validity of the questionnaire design. Cronbach's Alpha is a key metric for evaluating the reliability of questionnaire items. Empirical evidence suggests that a reliability coefficient of 0.70 or higher is considered acceptable for questionnaire items. As shown in Table 6, the Cronbach's Alpha values for each construct exceed 0.70, meeting the acceptable threshold. The results in Table 6 indicate that the five measurement scales used in the questionnaire are reliable.

Convergent and Discriminant Validity:

After assessing reliability, convergent and discriminant validity were evaluated to ensure the adequacy of the measurement model. Convergent validity refers to the extent to which multiple indicators of a construct are correlated and measure the same concept. It is commonly assessed using Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE). Cronbach's Alpha evaluates internal consistency, Composite Reliability measures the overall reliability of the construct, and AVE indicates the amount of variance captured by a construct relative to the variance due to measurement error. The values of CA, CR, and AVE for all constructs are presented in Table 7, demonstrating that the constructs satisfy the acceptable thresholds (CA and CR > 0.70, AVE > 0.50).

Furthermore, discriminant validity ensures that constructs are distinct from one another. According to SEM theory, the AVE of each construct should be greater than the variance shared between constructs. Both convergent and discriminant validity are verified through factor analysis [54].

Table 5. Respondent's information

Demographic Characteristics	Frequency	Percentage (%)
Gender		
Male	200	68 %
Female	60	32 %
Age		
18 to 24	150	50 %
25 to 30	150	50 %
Education		
Undergraduate	180	70.37 %
Masters	80	30.53 %

Table 6. Cronbach's Alpha values of the factors studied

Constructs	Cronbach's Alpha
AU	1.000
ITU	1.000
PEOU	0.808
PU	0.879
QU	0.870
SA	0.1000
STA	0.873
US	0.915

Table 8 shows that all diagonal values, which represent the square roots of the AVE, are greater than the off-diagonal values, indicating valid construct identification. According to SEM standards, the AVE should be at least 0.50, while Composite Reliability should exceed 0.70 [55][56]. These results support the presence of convergent and discriminant validity within the defined range for the factors being examined.

Loading and Cross-loading:

Discriminant validity was also measured by using the cross-loading criteria. In this method, we compare the outer loading of the construct on its own construct and on other constructs. Table 9 depicts the values of cross-loadings, in which all the loadings were higher on their own constructs than those on other constructs, which indicates discriminant validity.

Heterotrait-Monotrait Ratio (HTMT):

Discriminant validity is supposed to indicate the robustness of our model according to SEM conceptual dynamics. Researchers introduced a rigorous approach to further validating models. The approach is called Heterotrait-Monotrait Ratio (HTMT), in which we determine discriminant validity through a multitrait–multimethod matrix. The SEM measure of "Heterotrait-Monotrait ratio (HTMT)" correlates with discriminant validity [57]. HTMT values less than 0.85 are acceptable indicators of discriminant validity. The findings of Table 10 show that all the values of HTMT are acceptable, which confirms the discriminant validity. The results of this method are summarized in Table 10. All the values of the table are under the minimum criteria of 0.85, exhibiting discriminant validity.

Hypothesis Testing Result:

Table 11 shows the results of all hypotheses tested. As explained earlier, the SEM technique was primarily used to test the hypothesis. Specifically, every relation was tested that is present in the proposed research model, i.e., independent variables were put to test for determining their strength and significance. Table 11: 9 variables are coherent and pass the hypothesis testing. Specifically, among the factors studied, only usefulness appears to be significantly affecting the performance of students due to the acceptability of students towards eLearning. Thereby, the hypothesis related to usefulness is supported. On the contrary, the hypothesis related to perceived is rejected since it does not show a significant effect on performance impact. The results show that students are willing to continue using the eLearning mode due to the utility of the tools provided, but not due to the simplicity of usage. Overall quality proven strong predictor of performance impact on output; moreover, the link with intention to use is rejected, as sometimes students want to use e-Learning tools for different purposes and their goals and needs are different, so the P value shows results > 0.05 and the hypothesis was rejected. Similarly, our Actual Use claims are proven 50 percent right and 50 percent wrong, as some hypothesis P values are > 0.05, and some are not. As an end note, we can say that perceived usefulness is the strongest predictor of performance impact.

Foundation of Machine Learning Algorithm:

We applied a 10-fold cross-validation on several machine learning algorithms to evaluate the efficacy of the prediction models. Our approach aimed to develop a model that performs predictive analysis of performance impact using appropriate determinants. Cross-validation is a rigorous machine learning technique used to prevent biased results and ensure optimal reliability. The experimental setup for this model involved repeatedly splitting the data into testing and training sets.

Table 7. Convergent Validity Results for Reliability Testing

Constructs	CA	CR	AVE
AU	1.000	1.000	1.000
ITU	1.000	1.000	1.000
PEOU	0.808	0.874	0.636
PU	0.879	0.912	0.675
QU	0.870	0.906	0.658
SA	0.1000	0.1000	0.1000
STA	0.873	0.922	0.797
US	0.915	0.932	0.664

Table 8. Discriminant validity of the model

Construct	AU	ITU	PEOU	PU	QU	SA	STA	US
AU	1.000							
ITU	0.200	1.000						
PEOU	0.304	0.313	0.797					
PU	0.382	0.575	0.599	0.821				
QU	0.391	0.364	0.622	0.591	0.811			
SA	0.440	0.346	0.518	0.579	0.647	0.1000		
STA	0.268	0.583	0.445	0.670	0.509	0.432	0.893	
US	0.331	0.406	0.600	0.674	0.706	0.632	0.618	0.815

Table 9. Loading and Cross-loading results

	AU	ITU	PEOU	PU	QU	SA	STA	US
AU	0.728							
ITU		0.866						
PEOU1			0.763					
PEOU2			0.715					
PEOU3			0.812					
PEOU4			0.841					
PU1				0.777				
PU2				0.685				
PU3				0.891				
PU4				0.806				
PU5				0.825				
QU1					0678			
QU2					0.820			
QU3					0.861			
QU4					0.865			
QU5					0.628			
SA						0.737		
STA1							0.868	
STA2							0.875	
STA3							0.642	
US1								0.788
US2								0.851
US3								0.822
US4								0.723
US5								0.666
US6								0.632

Table 10. HTMT Analysis

	AU	ITU	PEOU	PU	QU	SA	STA	US
AU								
ITU	0.200							
PEOU	0.335	0.344						
PU	0.403	0.611	0.706					
QU	0.415	0.392	0.737	0.675				
SA	0.440	0.346	0.573	0.616	0.687			
STA	0.285	0.624	0.531	0.760	0.582	0.461		
US	0.342	0.422	0.688	0.749	0.783	0.654	0.693	

Table 11. Hypothesis Results

Hypothesis	factor1	factor2	factor3	factor4	Result
AU → ITU	-0.034	0.067	0.467	0.641	Reject
AU → SA	0.174	0.054	3.267	0.001	Accept
AU →STA	0.066	0.081	0.829	0.407	Reject
ITU →STA	0.486	0.059	8.223	0.000	Accept
PEOU →AU	0.028	0.075	0.208	0.835	Reject
PEOU →ITU	-0.085	0.072	1.166	0.244	Reject
PEOU → SA	0.053	0.053	0.989	0.323	Reject
PU → AU	0.242	0.106	2.189	0.029	Accept
PU → ITU	0.582	0.074	7.791	0.000	Accept
PU → SA	0.153	0.064	2.340	0.020	Accept
QU → AU	0.244	0.093	2.748	0.006	Accept
QU → ITU	0.072	0.096	0.695	0.487	Reject
QU→ SA	0.288	0.071	4.077	0.000	Accept
SA → STA	0.237	0.073	3.217	0.001	Accept
US → AU	-0.026	0.124	0.123	0.902	Reject
US → ITU	0.021	0.087	0.353	0.724	Reject
US → SA	0.235	0.079	3.011	0.003	Accept

Algorithm:

Artificial Neural Networks (ANN) Neural networks are computational models based on biological neural networks. They are made up of layers of neurons with input, hidden, and output layers. The information is processed using weighted connections and activation functions like Sigmoid or ReLU. The hidden layers update weights using backpropagation to learn data patterns. ANN is very efficient in extracting intricate patterns, particularly in large data sets, but it consumes a lot of computational power and is susceptible to overfitting unless properly regularized.

Support Vector Machine (SVM) is a supervised learning algorithm that determines the best hyperplane to classify various classes. It transforms input data to a high-dimensional space and attempts to find the hyperplane with maximum margin between two classes. Kernel functions like linear, polynomial, and radial basis function (RBF) enable SVM to deal with non-linearly separable data. SVM is powerful in high-dimensional space and resilient against overfitting, but computationally costly for big datasets and needs to be tuned carefully with respect to hyperparameters.

K-Nearest Neighbors (KNN) is a non-parametric, instance-based learner that identifies a data point according to the k-nearest neighbors. K Nearest Neighbors computes the proximity of the test instance and train samples in terms of metrics such as Euclidean or Manhattan distance, and classifies with the class that is dominant among the nearest points. KNN is not computationally complicated for small-sized datasets, but it starts being computationally expensive with larger datasets. It is sensitive to noisy features as well and needs an optimal k value for optimal performance.

Logistic Regression is a binary classification statistical technique that models the class probability using the sigmoid function. It uses a linear combination of input features and weights, and applies a sigmoid transformation to the result to output the probability of being in a class. Logistic Regression is efficient computationally, interpretable, and suitable for linearly separable data. But it imposes a linear link between independent variables and log-odds, so it won't be useful for complicated data sets.

Random Forest is an ensemble learning approach that builds many decision trees and combines their predictions. Every tree is trained on a bootstrapped version of the dataset, and at each split, a random subset of features is chosen to bring variability. The final prediction is made by majority voting among all trees. Random Forest performs well on high-dimensional data and is more robust against overfitting than a single decision tree. Nevertheless, it is computationally expensive when dealing with big data and is less interpretable than logistic regression.

Performance:

We utilized Random Mean Square Error (RMSE), Accuracy (Acc), and F-measure (F1) as key performance indicators for each iteration of the model. Table ?? presents the RMSE, Accuracy, and F1 measure of the neural network predictive model applied to the datasets.

The accuracy of classification models is measured by different metrics.

Accuracy is the ratio of correctly classified instances to the total number of instances, and it is represented by the formula.

T P +T N. Although accuracy gives a general idea of correctness, it can be deceptive for imbalanced datasets.

Precision is the number of well-predicted positive instances over the total predicted positives, calculated as

T P. Precision tells us how frequently the positive predictions are accurate. High precision implies a low proportion of false positives.

Recall, or sensitivity, is calculated as T P and refers to the percentage of true positives correctly identified. High recall represents a lower proportion of false negatives and is preferred where failure to capture positive cases is expensive. The F1 Score is the harmonic mean of precision and recall, given by 2× Precision×Recall. It gives a balanced estimate of a model's precision and recall, especially when dealing with imbalanced datasets. The Receiver Operating Characteristic (ROC) curve Area Under the Curve (AUC) measures the model's discriminative capability between classes. Increasing AUC reflects improving model performance, distinguishing positive and negative examples.

All these measures give useful information about model performance, from which practitioners can select the best classifier according to the particular requirements of the e-Learning tool acceptance.

The increasing integration of e-learning systems in the higher education context calls for an accurate interpretation of user acceptance to ensure the achievement of implementation. Several determinants, such as perceived usefulness (PU), perceived ease of use (PEU), technological self-efficacy, and institutional support, influence adoption choices. To analyze the behavior for prediction, we used machine learning models to predict user acceptance from historical data. Table 12 presents the refined experimental results that shows comparison evaluates the performance of Artificial Neural Networks (ANN), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Logistic Regression, and Random Forest (RF) based on various evaluation metrics for our datasets.

This analysis also highlights the relationships between independent and dependent variables, which are ordinal in nature. From the result obtained, we can make a rational interpretation. Random Forest model performs better than all other models with the best accuracy (79.49%) and recall (95.57%), indicating it performs well in identifying users who are accepting e-learning tools. Its F1-score (0.6530) indicates that it may be slightly less accurate in identifying true acceptance behavior. SVM (Support Vector Machine) also did an excellent job with 72.08% accuracy and 92.15% recall. That shows that it can effectively divide e-Learning users. The ANN model worked fairly well with 70.51% accuracy. This indicates that it is capable of dealing with intricate decision patterns in e-learning adoption. KNN performed worst at 59.80% accuracy. This implies that simply observing behavioral similarity may not necessarily suffice in predicting acceptance, particularly in alternative scenarios of institutions. Figure 3 shows box plot representations of Accuracy and Precision performance metrics for various machine learning models. The Random Forest model possesses the highest median accuracy, which represents a strong and consistent performance level. Correspondingly, the SVM and Neural Network models possess a moderate spread, which means that they are stable with some level of performance variability. The KNN and Logistic Regression models reflect lower median accuracy with a wider distribution, meaning that these techniques are less stable and more prone to data variation. Both SVM and Random Forest possess the highest median precision, meaning that these models are more effective in false positive reduction. The Neural Networks possess a moderate level of precision, meaning that there is good prediction balance but with possible misclassification of instances. Logistic Regression and KNN, however, possess a wider distribution range, meaning that there is greater variation in their precision levels.

Figure 4 exhibits a box plot representation of the Recall and F1-Score performance metrics for various machine learning models. Random Forest and Support Vector Machine (SVM) models have the highest recall values, which reflect their ability to accurately classify positive cases (i.e., accurately predict acceptance of an e-learning tool). The K-Nearest Neighbors (KNN) algorithm is very variable, which reflects its recall's dependence on dataset partitioning. Logistic Regression and Neural Networks have more stable recall, but lower median scores, which reflect possible failure to detect more positive cases. SVM and Random Forest have high F1-scores, which reflect a better precision-recall trade-off. Neural Networks' performance is moderate, i.e., good but possibly lower than that of SVM and Random Forest in idealized scenarios. KNN and Logistic Regression have high variability, which reflects high variability of their ability to balance false positives and false negatives.

Discussion:

The Technology Acceptance Model (TAM) indicates that Perceived Usefulness (PU) and Perceived Ease of Use (PEU) are key elements affecting the acceptance of e-learning. The outcomes from machine learning can be understood in these ways:

Perceived Usefulness (PU) and Model Performance: The Random Forest and SVM models exhibit strong recall values, indicating they accurately recognize users who consider e-Learning advantageous. This implies that users who view e-learning as helpful are reliably categorized correctly. Neural networks also achieve satisfactory performance, confirming that intricate decision-making patterns that involve cognitive factors are effectively represented.

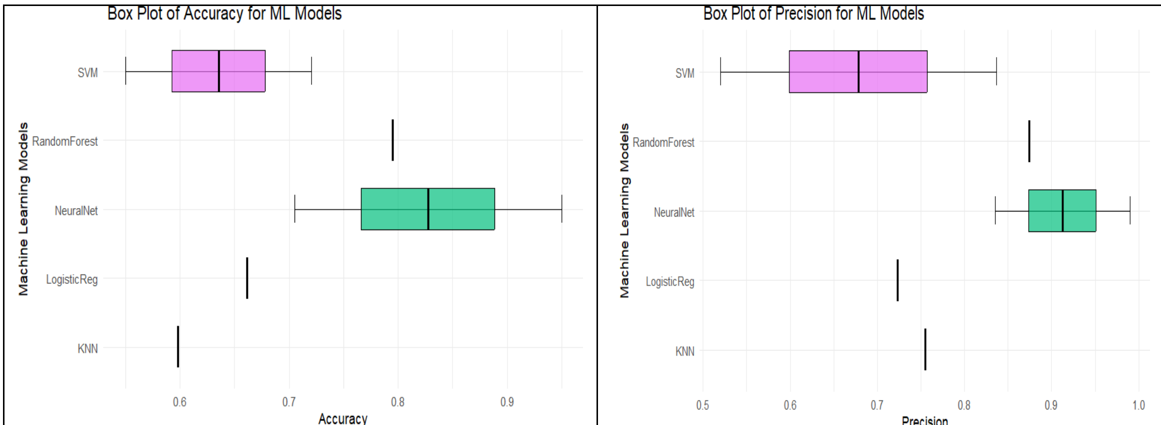
Perceived Ease of Use (PEU) and Behavioral Predictions: The KNN model, which is based on behavioral resemblance, does not achieve optimal performance. This might suggest that user-friendliness is not the only factor influencing acceptance and requires additional contextual analysis. The Logistic Regression model (accuracy: 66. 12%) offers insight into how organized decision-making affects adoption, although it has a reduced F1-score.

Behavioral Intent (BI): The Neural Network model (ANN) exhibited high precision (83. 53%), indicating that when it identifies a user as an adopter, it is very confident in this assessment. This is consistent with TAM, as behavioral intention typically comprises intricate cognitive and emotional elements. The elevated recall of Random Forest and SVM shows that users who plan to adopt e-learning tools are accurately recognized.

The distributions reveal performance variability across models.

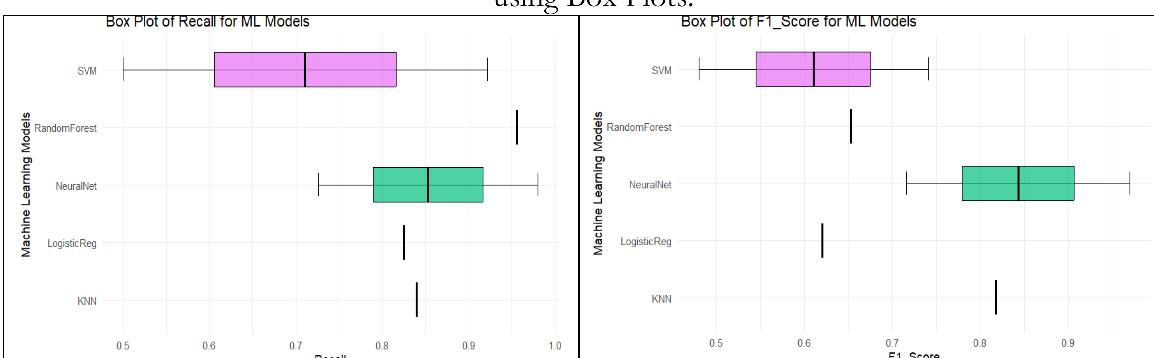
Table 12. Performance Metrics of Machine Learning Models for e-Learning Tool Acceptance

Model	Accuracy	Precision	Recall	F1 Score
Neural Network (ANN)	0.7051	0.8353	0.7260	0.7162
Logistic Regression	0.6612	0.7233	0.8252	0.6206
Support Vector Machine (SVM)	0.7208	0.8365	0.9215	0.7408
k-Nearest Neighbors (KNN)	0.5980	0.7548	0.8395	0.8181
Random Forest	0.7949	0.8742	0.9558	0.6530



(a) Box Plot of Accuracy for ML Models (b) Box Plot of Precision for ML Models

Figure 3. Comparison of Accuracy and Precision for various Machine Learning models using Box Plots.



(a) Box Plot of Accuracy for ML Models (b) Box Plot of Precision for ML Models

Figure 4. Comparison of Recall and F1 Score for various Machine Learning models using Box Plots.

Institutional elements, like training and assistance, may influence model predictions. Future studies could incorporate extra features to enhance model precision. Feature engineering (for instance, including user demographics and previous technology experience) could improve predictive capability. Random Forest and SVM models are the most efficient in forecasting acceptance of e-learning tools. Neural Networks offer a well-rounded prediction, identifying intricate behavioral patterns. KNN faces challenges with precision, indicating that mere behavioral similarity is insufficient for ensuring adoption. Future research ought to include external variables (EV) like institutional support, prior experience, and training programs to improve accuracy of predictions.

Limitations:

While this study has illuminated critical determinants influencing student acceptance of e-Learning tools and their subsequent impact on academic performance, it is essential to acknowledge certain inherent limitations related to the research design and data collection methodologies. Notably, the participants sampled from specific universities in Pakistan and the United States may not fully represent the global student demographic, thereby limiting the generalizability of the findings. Furthermore, the use of advanced analytical techniques, specifically Structural Equation Modeling (SEM) and Machine Learning (ML), although robust, introduces methodological constraints and the potential for overfitting.

The cross-sectional nature of the study allows for the examination of relationships at a specific point in time but does not establish causality. Additionally, the study primarily focused on specific e-Learning tools, which may limit a comprehensive understanding of diverse experiences across various platforms. The reliance on survey data also introduces the potential for self-report bias.

Despite these limitations, this research offers valuable insights into the adoption of e-Learning tools and their impact on performance, providing a solid foundation for future investigations in the field of education.

Conclusion:

The findings of this study have significant implications and practical relevance. Firstly, the study has demonstrated that key determinants in the e-Learning process can impact performance. It analytically illustrates the relationship between independent and dependent variables. The results from the predictive analysis show that the factors investigated have a considerable influence on performance.

Secondly, the hypothesis testing results suggest that Usability and Quality are critical factors in enhancing and improving individual performance in an e-Learning academic environment. This insight can assist policymakers in recommending and emphasizing the inclusion of Usability and Quality parameters in Online Higher Education.

Thirdly, validating our model through a rigorous predictive analysis approach was essential.

In addition to these broad findings, we have identified several key points: 1. Student performance is a complex concept that must be modeled using mathematical or analytical methods to assess the efficacy of tools. 2. While e-Learning tools positively impact education, there are research gaps that need to be addressed to fully capitalize on the benefits of face-to-face (F2F) conventional learning. 3. The results of the hypothesis testing mostly support the emphasis on usability and quality factors within the e-Learning environment.

It was observed that the RMSE (0.75), Accuracy (0.705), and F1 measure (0.71) of the ANN model were sufficiently high, affirming the significance of Perceived Usability, Perceived Ease of Use, Overall Quality, and Usability as important parameters. Additionally, the sensitivity analysis of input variables highlighted the importance of these factors. Therefore, it can be concluded that the impact and significance of an individual's performance in e-Learning are driven by the factors analyzed in this study. For future replication, researchers are encouraged to consider incorporating alternative acceptance models alongside or instead of the Technology Acceptance Model (TAM) used in this study. The choice of TAM in our study was based on its well-established reputation in technology adoption and acceptance research. TAM has been widely applied to understand user behaviors and preferences regarding various technologies, including e-Learning tools. Constructs such as Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) provided relevant insights into the factors influencing students' decisions about e-Learning tool acceptance. However, exploring alternative models, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) or the Innovation Diffusion Theory (IDT), may offer additional theoretical perspectives and insights. These models encompass diverse constructs that could provide a deeper and more nuanced understanding of e-Learning tool acceptance in different contexts. The selection of the acceptance model should align closely with the specific research objectives and the unique characteristics of the target population and educational environment.

This study can be expanded to future work by adding longitudinal datasets that will help to understand the changing behavior of students and the long-term effect of the adoption of eLearning on academic performance. Also, more sophisticated deep learning algorithms and explainable AI systems can be considered to improve the accuracy of predictions and understanding of findings. Lastly, the model can be extended to incorporate other contextual variables like socio-economic background, digital literacy, and instructor effectiveness to have a more holistic picture of eLearning success.

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