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Determining the most critical factors affecting E-learning in some Saudi universities by using statistical methods

Hanaa Abu-Zinadah[a,*], Salwa L. AlKhayyat[b], & Eman Alhawiti[a]

[a] *University of Jeddah, College of Science, Department of Mathematics and Statistics, Jeddah, Saudi Arabia*
[b]*University of Jeddah, College of Computer Science and Engineering, Department of Computer Science & Artificial Intelligence, Jeddah, Saudi Arabia*

Abstract

In higher education, the shift to e-learning reflects the need for flexibility, accessibility, and technological advancements. This shift enables students to study anywhere and at any time, making education more adaptable and inclusive of individual needs. The global COVID-19 pandemic accelerated the shift to e-learning in higher education, making faculty acceptance a key factor in its success. This study aims to identify factors influencing the orientations of faculty members in some Saudi universities toward e-learning (blended learning) as a viable alternative to traditional instruction. Statistical methods, including Decision Tree, Neural Network, and Logistic Regression analyses, were used to determine these factors. The analysis revealed that the most influential factors shaping faculty attitudes toward e-learning were the suitability of teaching from home, the adherence to lecture schedules, the availability of lecture recordings, the need for additional time, and the view of blended learning as a solution during crises. The results of blended learning in higher education can show improved student performance, increased engagement, and greater flexibility in learning. Combining online and face-to-face instruction allows learners to study at their own pace while still benefiting from in-person interaction. These findings suggest that technological readiness, time discipline, and positive perceptions of blended learning enhance faculty acceptance of e-learning. These findings suggest that technological readiness, time discipline, and positive perceptions of blended learning enhance faculty acceptance of e-learning.

Keywords: Blended learning; Decision tree; Electronic Learning; Logistic regression; Neural networks.

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1. Introduction

A profound digital transformation has characterized the 21st century, and higher education has been no exception. The integration of technology into teaching and learning has shifted from a marginal interest to a central strategic priority for universities worldwide (Benavides et al., 2020 & Rahmadi, 2024). This shift was further accelerated by the COVID-19 pandemic, which forced the rapid adoption of emergency distance education and e-learning models (Bond et al., 2021).

In Saudi Arabia, this global trend aligns with the nation's Vision 2030, which emphasizes building a modern, high-quality educational system as the foundation for future development. Saudi universities have invested substantially in digital infrastructure and e-learning platforms. However, the effectiveness of these investments depends not only on the tools themselves but also on faculty members' willingness and ability to employ them effectively (Al-Gahtani, 2016). Since the educational process relies on two fundamental pillars, the faculty member as the sender and the students as the receivers, this paper focuses on the faculty member (the sender) as the key controlling element in the effectiveness of e-learning adoption and the quality of its outcomes.

With respect to the development of e-Learning systems in three large universities in Saudi Arabia, as presented by (Alhabeeb & Rowley, 2017). This study aims to examine the management of eLearning systems from the perspectives of key players. Also, compare the results with studies conducted elsewhere in the world.

[*] Corresponding author.
E-mail address: hhabuznadah@uj.edu.sa

This paper also seeks to answer the following research questions:

a. What are the most influential factors that predict faculty members' inclination to adopt e-learning as an alternative to traditional education?

b. How do advanced analytical techniques (such as the Decision Tree algorithm versus Neural Networks) compare in identifying these critical factors?

The studies presented by (Fauzi, 2020) have shown the state of e-learning in higher education institutions during the COVID-19 pandemic through a bibliometric analysis of research published in the Web of Science database between 2019 and 2020. It aims to identify the main research trends and influential topics in this field and to provide a vision for the future of e-learning research after the pandemic. The study found several key themes related to the development of e-learning and emphasized the importance of its findings in guiding researchers and policymakers to strengthen and sustain e-learning during times of crisis.

In the Saudi context, (Alruwaili, 2021) explores Saudi EFL teachers' perceptions of blended learning and its impact on student engagement compared to traditional teaching methods. A total of 42 teachers were selected to represent diversity in gender, experience, and technological competence. The researcher used a qualitative design with open-ended questionnaires and thematic analysis. Findings revealed that blended learning moderately enhances student engagement, but it faces technological and organizational challenges, such as limited digital infrastructure and varying levels of teachers' digital skills. Despite these obstacles, teachers expressed cautious optimism about the potential of blended learning to improve educational outcomes if it is properly supported and systematically implemented in Saudi Arabia.

A systematic review was conducted by (Meng et al., 2023) to examine the effectiveness of online learning in higher education during the COVID-19 pandemic. The review analyzed 25 empirical studies published between 2020 and 2023 to identify overall outcomes and the key factors influencing online learning success. Findings revealed mixed results: while some studies reported that online learning improved flexibility and accessibility, the majority indicated lower effectiveness compared to traditional instruction, mainly due to limited interaction, technological challenges, and low digital readiness among instructors and students. Factors such as course design quality, institutional support, and technological infrastructure were found to be critical determinants of learning outcomes. Despite these challenges, the review concluded that online learning holds potential as a complementary or blended approach in higher education, provided that pedagogical design and digital infrastructure are strengthened to enhance student engagement and learning effectiveness.

As noted in (Wen et al. 2020), the COVID-19 pandemic compelled schools to transition from traditional to online education. A survey of 498,481 teachers in Guangdong, China, was conducted to assess their views on online teaching. Results showed that over 80% were satisfied with online resources and 68% with platforms and software. Researchers used Chi-square analysis to examine differences between urban and rural teachers, then built a neural network model that predicted teacher satisfaction with 90% accuracy. The study concluded that the pandemic accelerated the adoption of online education and highlighted the importance of understanding the factors affecting teachers' satisfaction and readiness for the future.

The study presented by (Özbek et al., 2021) aimed to identify the key variables and factors that affect university students' perceptions and decisions about the effectiveness of online learning. To this end, 821 university students were surveyed. Their willingness and attachment to online education, socioeconomic level, and gender were tested using logit regression analysis to build a model that predicts university students' decisions about the efficiency of online education. Age, gender, high school graduation, willingness to pursue Online Education, and attachment to Online Education are among the variables in the logit regression model that significantly predict university students' decision about whether they consider online education to be efficient or not. When analysing the result of classifying students whether they consider online education efficient or not using the logit regression model, 291 of the 409 students in the group who consider education efficient were classified correctly and 118 of them were classified inaccurately, with the rate of correct classification being 71.1%.

Identifying variables and factors influencing e-learning in some Saudi universities is our objective in this study. Design an intelligent predictive model by using machine learning algorithms such as Decision tree and Neural Network and evaluate the predictive model's accuracy and compare its results with those from traditional evaluation methods. Propose practical and strategic recommendations for university decision makers to improve the quality of blended learning based on the model's results.

The paper is summarized as follows: In section 2, the Materials and Methods Structure is discussed as follows: 2.1 Assumptions of decision tree analysis and its numerical results, 2.2. Neural network analysis and its numerical results, 2.3 Logistic regression analysis using the outputs of both classification approaches: decision tree and artificial neural networks. In section 3, the conclusion and the important recommendations.

2. Materials and Methods Structure

In this study, data were gathered through a questionnaire distributed by all available methods, aiming to assess faculty members' attitudes toward e-learning and blended learning as alternatives to traditional education. The data were analyzed using three advanced statistical techniques: Decision Tree, Neural Networks, and Logistic Regression, to identify factors influencing faculty members' acceptance of e-learning as a viable substitute for in-person instruction. All analyses were performed with SPSS software, version 25. The target population included 1,003 full-time faculty members at 30 public universities across various regions of the Kingdom of Saudi Arabia. To ensure geographically representative participation, a stratified random sampling method was used. Universities were first divided into five main strata based on the Kingdom's regions: Northern, Southern, Eastern, Western, and Central. A random sample of faculty members was then invited from each region. This stratified approach ensured that the final sample represented faculty from all areas of the Kingdom, improving the generalizability of the results across Saudi universities. Data collection took place from 2022 to 2025.

For clarity and brevity in presenting results, the 30 survey items on experiential and perceptual measures were assigned variable codes (X1 to X30). Table 1 includes a detailed key linking each code to its original name. These codes are used in the figures in the results chapter.

Table 1. Study variables

Variable Code	Original Variable Name
X1	Training on the platform before the pandemic
X2	Activation of e-learning before the pandemic
X3	Use of platform tools during the pandemic
X4	Quality of internet used for teaching before the pandemic
X5	Quality of internet used for teaching during the pandemic
X6	Teaching from home during the pandemic
X7	Effect of internet issues on delivering lectures on time
X8	Adherence to lecture schedules
X9	Management follow-up on lectures
X10	Student adherence to lecture times
X11	Lecture recording
X12	Providing feedback to students
X13	Communication with students
X14	Lecture congestion or scheduling conflicts
X15	Student participation and interaction
X16	Facilitating course content through Blackboard technologies
X17	Suitability of courses for online teaching
X18	The need to give extra lectures
X19	Difficulty of exams and grading during e-learning
X20	Limited time during online exams
X21	Use of e-learning after the pandemic
X22	Opinions on e-learning during the pandemic
X23	e-learning and blended learning vs. traditional education (dependent variable DV)
X24	Blended learning as a solution for crises
X25	Gender
X25	University
X26	College
X28	Major
X29	Academic rank
X30	University region

2.1. Decision Tree analysis

This section explains the main concepts of the Decision Tree method and how it uses data. The Decision Tree is a structured, tree-like model that helps analyze relationships and predict outcomes. It begins with a root node, which splits data based on the most important variable, then branches out to show decision rules and leaf nodes representing results. The model uses splitting criteria such as Gini Index or Information Gain to choose the best variable for each split. By recursive partitioning, the data is divided repeatedly until each group is as uniform as possible. To avoid overfitting, the tree is simplified through pruning, and the importance of variables is assessed by their impact on prediction accuracy. Overall, the Decision Tree is a useful method for identifying key factors and visualizing decision-making processes.

2.1. 1 Assumptions of Decision Tree analysis

Decision Tree analysis assumes that observations are independent and that predictor variables provide enough variation to enable meaningful classification (Han, Kamber, & Pei, 2012). It does not require the data to follow a specific statistical distribution, making it suitable for social science and educational research (Loh, 2011). The method can handle both categorical and continuous variables, which fits the nature of this study's dataset, including demographic and attitudinal factors related to faculty adoption of e-learning. To prevent overfitting and enhance the model's generalizability, the tree was pruned using optimal depth and node limits (Rokach & Maimon, 2014).

2.1.2 The result of decision tree analysis

The results are summarized in Table 2, which presents the top 13 predictors ranked by importance and their corresponding normalized importance percentages.

Table 2. Decision Tree Variable Importance Ranking

Rank	Independent Variable	Variable Code	Importance	Normalized Importance (%)
1	Blended learning as a solution for crises	X24	0.315	100.0%
2	Adherence to lecture schedules	X8	0.269	85.6%
3	Lecture congestion or scheduling conflicts	X14	0.239	75.9%
4	Use of e-learning after the pandemic	X21	0.233	74.0%
5	The need to give extra lectures	X18	0.229	72.7%
6	Teaching from home during the pandemic	X6	0.223	70.8%
7	Effect of internet issues on delivering lectures on time	X7	0.219	69.6%
8	Suitability of courses for online teaching	X17	0.167	53.0%
9	Facilitating course content through Blackboard technologies	X16	0.157	49.8%
10	Quality of internet used for teaching during the pandemic	X5	0.154	49.0%
11	Student participation and interaction	X15	0.152	48.5%
12	Communication with students	X13	0.152	48.5%
13	Lecture recording	X11	0.149	47.5%

Based on the data analysis presented in Table 2, the most influential factor is X24 (Blended learning as a solution for crises), with a normalized importance of 100%, indicating that faculty members strongly value blended learning during situations when traditional face-to-face teaching becomes difficult or impossible, such as political unrest, pandemics, or natural disasters. The second most important factor is X8 (adherence to lecture schedules), at 85.6%, showing that commitment to planned lecture times increases faculty willingness to adopt and rely on e-learning. In contrast, lecture congestion or scheduling conflicts (X14), with a contribution of 78.5%, emphasize that reducing timetable overlaps plays a crucial role in supporting the transition to blended learning. Moreover, the continued use of e-learning after the pandemic (X21), at 74.0%, reflects a long-term trend toward integrating digital tools in teaching beyond emergency conditions. The need to give additional lectures (X18), with an importance of 72.7%, also appears as a major advantage of e-learning, enabling faculty to complete curriculum requirements more flexibly. Teaching from home during the pandemic (X6), at 70.8%, highlights the convenience and continuity that e-learning provides, while the effect of internet issues on delivering lectures on time (X7), at 69.6%, stresses the importance of reliable connectivity for sustaining effective instruction. Additionally, the suitability of courses for online teaching (X17), at 53.0%, demonstrates that the nature of the course itself affects how smoothly blended learning can be implemented. Facilitating course content through Blackboard technologies (X16), with a contribution of 49.8%, further underlines the essential role of university learning platforms in supporting teaching activities. Internet quality during the pandemic (X5), at 49.0%, contributes to faculty satisfaction with digital teaching environments, while student participation and interaction (X15), also at 48.5%, reinforce the importance of maintaining learner engagement. Communication with students (X13), at 48.5%, remains a key driver of successful e-learning, as regular interaction strengthens teaching effectiveness. Lastly, lecture recording (X11), with an importance of 47.5%, plays a valuable role in supporting student revision and ensuring flexible access to learning materials. Overall, these combined results demonstrate that acceptance of e-learning is shaped by crisis-driven necessity, time management, course suitability, technological readiness, and the perceived pedagogical value of blended learning. Table 3 shows the model's accuracy in classifying respondents according to the dependent variable X23 (agreement or disagreement with e-learning)

Table 3. Classification table in the Decision Tree analysis

Classification

	Predicted		
Observed	**Disagree**	**Agree**	**Percent Correct**
Disagree	231	21	91.7%
Agree	11	740	98.5%
Overall Percentage	24.1%	75.9%	96.8%

Growing Method: CRT
Dependent Variable: X23 (DV)

The model correctly classified 91.7% of those who disagreed and 98.5% of those who agreed, with an overall accuracy of 96.8%. This indicates that the Decision Tree model demonstrates a high predictive power and excellent ability to distinguish between the two groups.

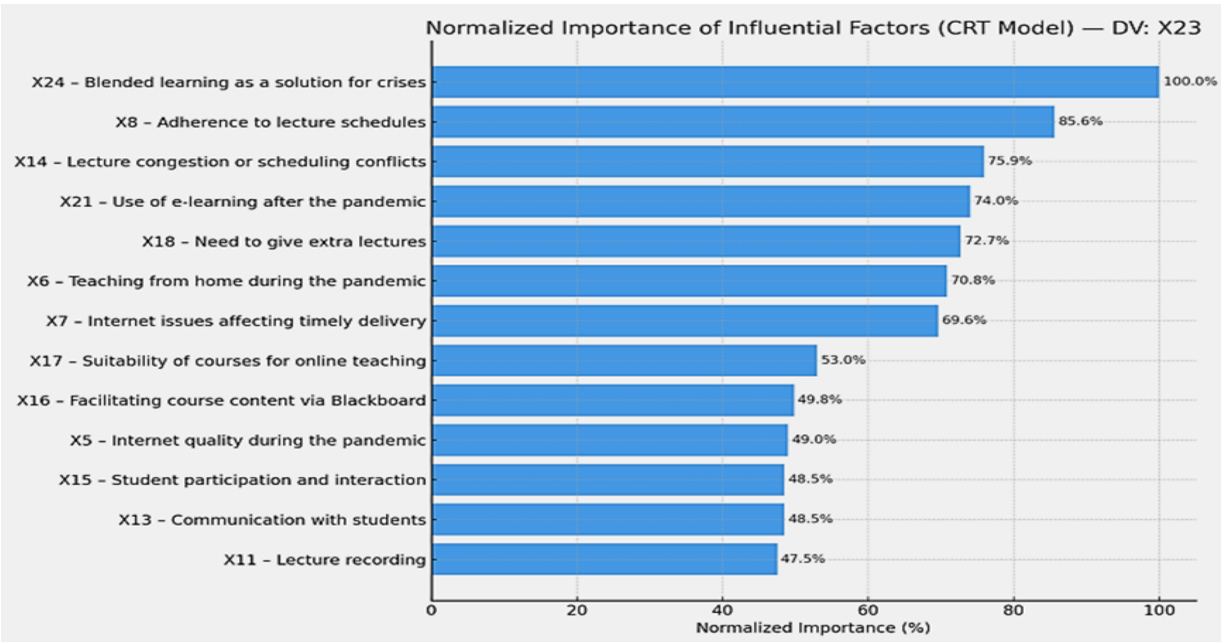

Figure 1. Normalized importance chart in the Decision Tree analysis

Figure 1 illustrates the relative contribution of each independent variable in predicting the dependent variable (X23). Each bar represents a predictive factor, with its length indicating the normalized strength of its contribution. Thus, longer bars reflect greater influence in explaining faculty members' orientations toward e-learning (specifically blended learning).

2.2. Neural network analysis

This section illustrates the main concepts of the neural network method and its applications to the data. The Neural Network (NN) method simulates the human brain's learning process through interconnected units called neurons. These neurons are organized into input, hidden, and output layers, where each connection has a weight that is adjusted during training to improve prediction accuracy. Learning occurs through backpropagation, using optimization algorithms such as Gradient Descent, and activation functions (e.g., ReLU, Sigmoid) allow the model to capture nonlinear relationships. This method is effective for detecting complex patterns and predicting outcomes. In this study, it was applied to identify the key factors influencing faculty members' acceptance of e-learning.

2.2.1. Assumptions of neural network analysis

Neural network analysis assumes that the data are representative and contain sufficient variability to allow the model to learn meaningful patterns (Haykin, 2009). It requires that the observations are independent and that the relationships among variables can be learned through non-linear transformations rather than predefined equations (Bishop, 1995). The method does not assume normality, linearity, or homoscedasticity, which makes it suitable for complex behavioral and educational data (Sarle, 1994). In this study, the neural network model was trained and validated on an adequately large and diverse dataset to ensure reliable generalization and avoid overfitting.

2.2.2. The result of neural network analysis

The results are summarized in Table 4, which presents the top 12 predictors ranked by importance and their corresponding normalized importance percentages.

Table 4. Top Predictors of Faculty Agreement Identified by the Neural Network Model

Rank	Independent Variable	Variable Code	Importance	Normalized Importance (%)
1	Limited time during online exams	X20	0.067	100.0%
2	Adherence to lecture schedules	X8	0.061	92.1%
3	The need to give extra lectures	X18	0.059	88.5%
4	Major	X28	0.057	86.0%
5	Use of e-learning after the pandemic	X21	0.049	74.0%
6	Lecture recording	X11	0.048	72.1%
7	The need to give extra lectures	X4	0.048	71.6%
8	Adherence to lecture schedules	X24	0.048	71.5%
9	Student adherence to lecture times	X10	0.042	62.6%
10	Academic rank	X29	0.039	58.2%
11	Suitability of courses for online teaching	X17	0.038	56.6%
12	College	X27	0.037	54.9%
13	Effect of internet issues on delivering lectures on time	X7	0.033	49.0%
14	Lecture congestion or scheduling conflicts	X14	0.032	48.3%
15	Teaching from home during the pandemic	X6	0.032	47.5%
16	University	X26	0.032	47.4%

The results presented in Table 4 indicate that X20 (limited time during online exams), with the highest relative importance of 100%, is the strongest factor influencing faculty members' attitudes toward e-learning, suggesting that time pressure in online examinations plays a decisive role in shaping acceptance of blended learning. The second factor, X8 (adherence to lecture schedules), at 92.1%, highlights the importance of time discipline in supporting positive orientations toward digital teaching. The third factor, X18 (the need to give extra lectures), at 88.5%, reflects the role of teaching workload in influencing acceptance. This is followed by X28 (major), at 82.5%, indicating that academic specialization contributes to differences in attitudes. The factor X21 (use of e-learning after the pandemic), at 74%, demonstrates a continued willingness to integrate digital tools beyond the crisis period. X11 (lecture recording), at 71.4%, emphasizes the value of providing students with flexible access to course materials. The factor X4 (the need to give extra lectures), at 71.6%, reinforces the impact of workload demands. X24 (adherence to lecture schedules), at

70.8%, shows again that timetable organization remains central. X10 (student adherence to lecture times), at 62.6%, illustrates how student discipline shapes faculty perceptions. X29 (academic rank), at 58.2%, suggests that seniority affects the adoption of blended learning. X17 (suitability of courses for online teaching), at 58.6%, highlights that the nature of the course determines its adaptability to e-learning. X27 (college), at 54.3%, indicates institutional differences among colleges. The factor X7 (effect of internet issues on delivering lectures on time), at 49%, underscores the critical role of stable internet connectivity. X14 (lecture congestion or scheduling conflicts), at 48.7%, shows that reducing timetable clashes supports adoption. X6 (teaching from home during the pandemic), at 47.5%, reflects the convenience and continuity offered by remote instruction. Finally, X26 (university), at 47.4%, suggests that institutional policies and digital readiness across universities shape acceptance levels. Overall, these combined results demonstrate that faculty attitudes toward e-learning are influenced by a complex interaction of time constraints, workload, technological readiness, course characteristics, academic background, and institutional context.

Table 4 shows the predictive performance of the neural network model in classifying the training and testing samples according to the dependent variable X23 (agreement or disagreement with e-learning (blended)).

Table 5. Classification table in Neural Network analysis

Classification

		Predicted		
Sample	**Observed**	**Disagree**	**Agree**	**Percent Correct**
Training	Disagree	163	11	93.7%
	Agree	3	512	99.4%
	Overall Percent	24.1%	75.9%	98.0%
Testing	Disagree	72	5	93.5%
	Agree	0	235	100.0%
	Overall Percent	23.1%	76.9%	98.4%

Dependent Variable: X23 (DV)

The model achieved a high accuracy of 98.0% for the training sample and 98.4% for the testing sample, indicating that the neural network demonstrates strong predictive efficiency and stable generalization performance. Figure 2 shows the relationship between Sensitivity and 1 – Specificity.

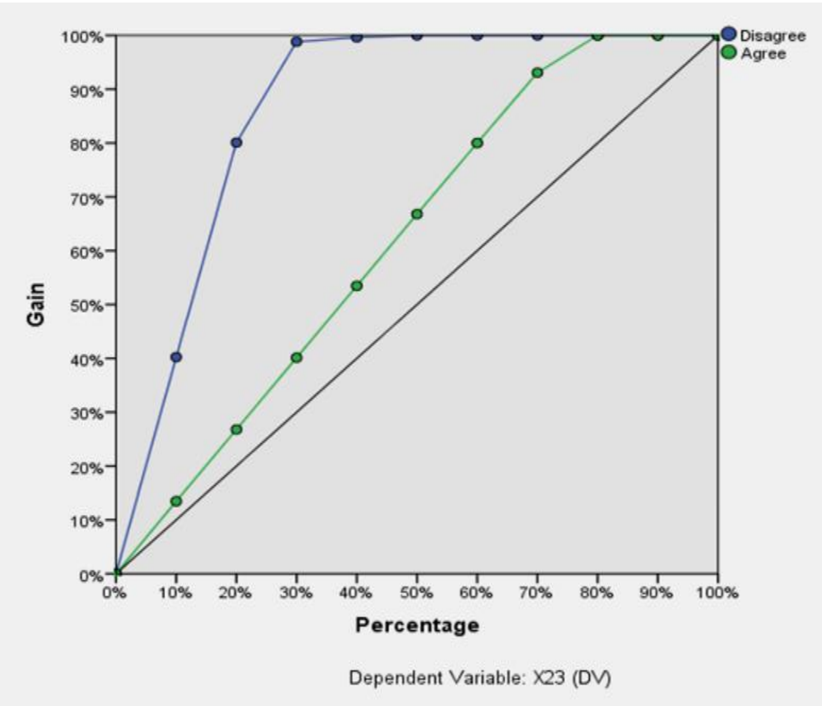

Figure 2. ROC Curve

The closer the curve is to the upper-left corner, reflects the model's strong predictive performance and its ability to distinguish between the two groups. In this case, the curve closely follows the top and left borders, indicating high accuracy and excellent efficiency in predicting agreement or disagreement with e-learning (blended learning).

Figure 3 shows the relationship between the percentage of predicted samples and the cumulative gain rate.

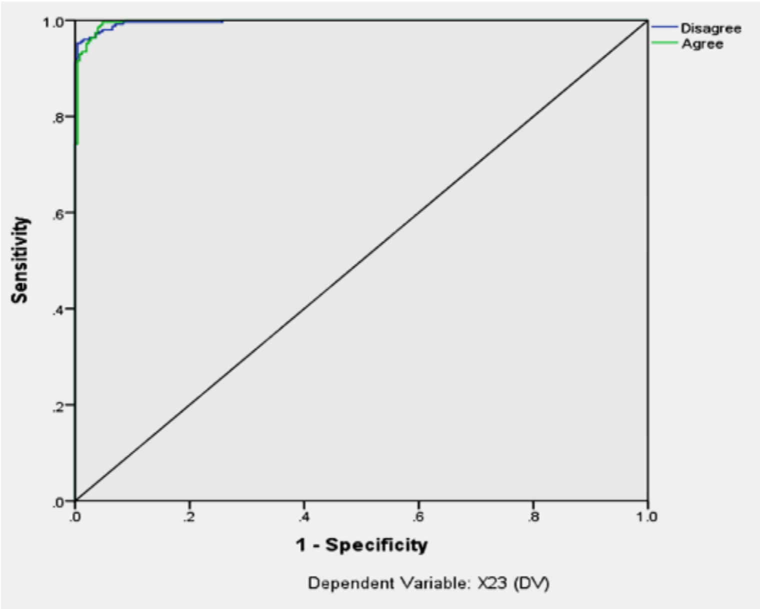

Figure 3. Cumulative Gains Chart

The higher the curve rises above the diagonal (random line), the better the model performs compared to random prediction. In this figure, the Disagree curve rises sharply and approaches the upper boundary, indicating that the model has a strong ability to correctly identify the "disagree" group, while also performing well in predicting the "agree" group. This demonstrates the model's effectiveness and high predictive accuracy in identifying faculty orientations toward e-learning.

Figure 4 shows the contribution of each independent variable in predicting the dependent variable X23 (agreement or disagreement with e-learning).

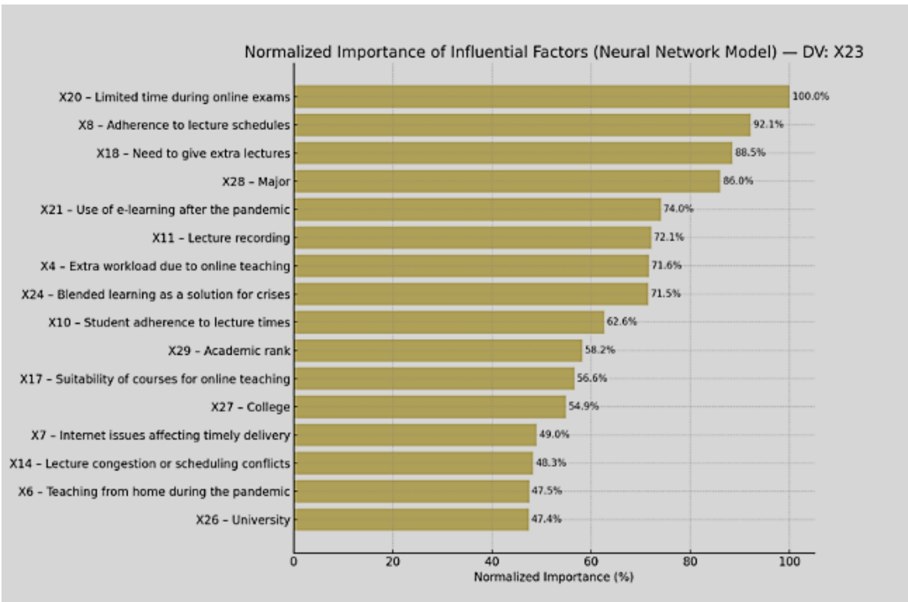

Figure 4. Normalized Importance Chart

Figure 5 represents the Neural Network Architecture used to predict the dependent variable X23.

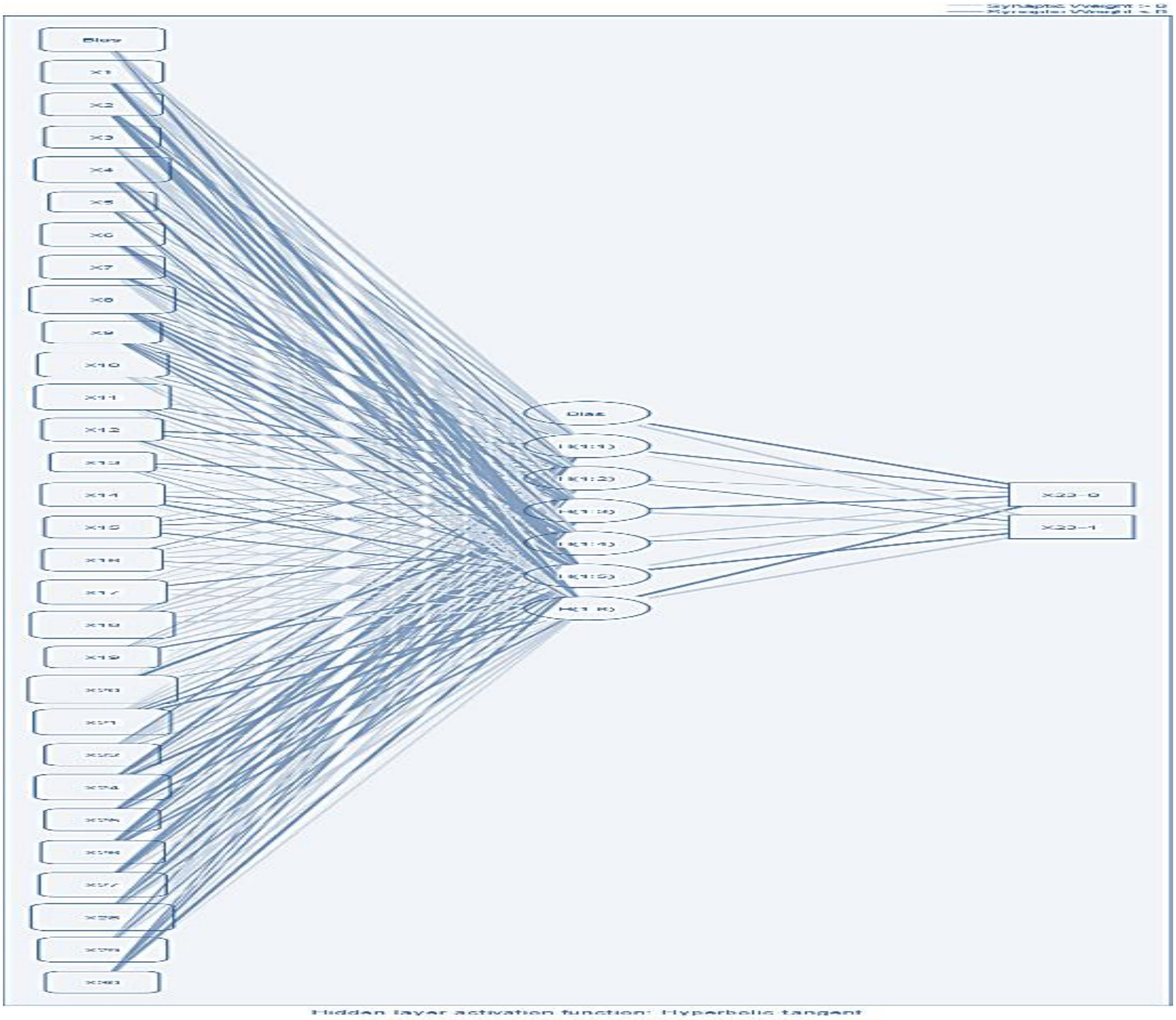

Figure 5. Neural Network Architecture Diagram

- The lines connecting input variables to the hidden layer represent the weights assigned to each connection. These weights determine the strength and influence of each variable on the hidden units.
- The lines between the hidden layer and the output layer represent the transformed weights that determine how the internal processing influences the final classification.
- The density and number of lines indicate that the model evaluates all possible connections between inputs and hidden neurons to produce the most accurate prediction.
- Even though the numerical weight values are not shown, each line signifies that the corresponding variable contributes to the prediction process.

The network consists of an input layer containing the independent variables (X1–X30), a hidden layer with six neurons using the Hyperbolic Tangent activation function, and an output layer employing the Softmax function to classify the two categories (Agree/Disagree). The diagram illustrates the flow of information between layers, where the thickness of the lines indicates the strength of connections, reflecting the model's ability to analyze patterns and predict faculty orientations toward e-learning (blended learning).

2.3. Logistic Regression Analysis

This section outlines the key concepts of the logistic regression method and its application to the data. Logistic regression is a statistical method used to predict the probability of a binary outcome (yes/no) based on independent variables. It utilizes the logistic function to convert outputs into probabilities between 0 and 1, and the results are interpreted using odds ratios to demonstrate the effect of each variable on the outcome.

2.3.1. Assumptions of neural network analysis

Logistic regression analysis assumes that the dependent variable is binary and that the observations are independent (Hosmer, Lemeshow, & Sturdivant, 2013). It also assumes a linear relationship between the continuous independent variables and the log odds of the dependent variable (Menard, 2002). The model requires that multicollinearity among predictors be minimal, ensuring that each variable contributes uniquely to the prediction. Logistic regression does not require normality of the predictors, making it suitable for social science and educational research data (Pallant, 2020). In this study, these assumptions were checked and satisfied prior to conducting the logistic regression analysis.

2.3.2. The results of the logistic regression combined with the decision tree

To validate these findings, the top predictors from the decision tree were entered into a Binary Logistic Regression model to test their statistical significance and direction of influence. The results are summarized in Table 6.

The logistic regression model revealed 6 significant predictors ($p < 0.05$) that positively influenced faculty agreement with e-learning (blended learning):

The logistic regression results indicate that the model effectively identifies the factors influencing faculty members' orientations toward e-learning (blended learning). Variables X6, X8, X11, X18, and X24 show positive and statistically significant effects ($p < 0.05$), meaning that higher values of these variables increase the likelihood of agreement with e-learning. In contrast, X21 has a negative and significant relationship (B = -0.717, OR = 0.488), suggesting that a lower tendency to use e-learning after the pandemic reduces the probability of agreement. Overall, the findings highlight that adherence to lecture schedules (X8) and viewing blended learning as a solution for crises (X24) are the most influential positive factors supporting faculty acceptance of e-learning.

The Equation of the model:

$$\log\left(\frac{\hat{\rho}}{1-\hat{\rho}}\right) = -3.891 - 0.717(X21) + 0.837(X24) + 0.737(X8) + 0.551(X18) + 0.511(X6) + 0.487(X11)$$

The equation explains the probability of faculty members supporting e-learning (blended learning) based on six independent variables. Constant (−3.891) indicates a low baseline probability of support when all variables are zero. X21 (−0.717) negative effect decreases the likelihood of support. X24 (+0.837) strongest positive effect — faculty who view blended learning as a solution for crises are more likely to support e-learning. X8 (+0.737) adherence to lecture schedules increases support. X18 (+0.551) needs extra time to positively influence support. X6 (+0.511) teaching suitability from home has a positive impact. X11 (+0.487) availability of lecture recordings increases the likelihood of support.

Summary: Higher values of X24, X8, X18, X6, and X11 increase faculty support for e-learning, while X21 slightly reduces it.

Table 6. Summary of Logistic Regression Based on Decision Tree Predictors

Predictor Variable	B (Estimate)	SE	OR [Exp(B)]	p-value (Sig.)
Constant	-3.891	0.468	0.020	0.000
X6	0.511	0.245	1.667	0.037
X8	0.737	0.272	2.089	0.007
X11	0.487	0.241	1.628	0.043
X18	0.551	0.217	1.735	0.011
X21	-0.717	0.259	0.488	0.006
X24	0.837	0.271	2.309	0.002

2.3.3. The results of the logistic regression combined with the neural network

To validate these findings, the top predictors from the neural network were entered into a Binary Logistic Regression model to test their statistical significance and direction of influence. The results are summarized in Table 7 below.

Table 7. Logistic Regression Summary Based on Neural Network Predictors

Predictor Variable	B (Estimate)	SE	OR [Exp(B)]	p-value (Sig.)
Constant	-4.168	1.005	0.015	0.000
X6	0.709	0.241	2.031	0.003
X8	0.814	0.277	2.257	0.010
X10	0.526	0.245	1.693	0.032
X11	0.618	0.239	1.855	0.010
X18	0.586	0.215	1.796	0.007
X20	-0.598	0.222	0.550	0.007
X24	0.670	0.276	1.954	0.015
X27	0.336	0.099	1.400	0.001
X28	-0.145	0.069	0.865	0.036

The logistic regression analysis identified 9 significant predictors ($p<0.05$) influencing faculty agreement with e-learning.

The logistic regression results indicate that the model accurately explains the factors influencing faculty members' orientations toward e-learning (blended learning). Variables X6, X8, X10, X11, X18, X24, and X27 show positive and statistically significant effects ($p < 0.05$), meaning that higher values of these variables increase the likelihood of agreement with e-learning. In contrast, variables X20 and X28 have negative and significant effects, suggesting that limited time during online exams (X20) and academic major (X28) reduce the probability of agreement. Overall, the results highlight that adherence to lecture schedules (X8), lecture recording (X11), and teaching from home (X6) are among the strongest factors promoting e-learning adoption, while time constraints and academic discipline weaken this orientation.

The Equation of the model:

$$\log\left(\frac{\hat{\rho}}{1-\hat{\rho}}\right) = -4.168 - 0.598(X20) - 0.145(X28) + 0.814(X8) + 0.709(X6) + 0.670(X24) + 0.618(X11) + 0.586(X18) + 0.526(X10) + 0.336(X27)$$

This equation represents the probability of faculty members supporting e-learning (blended learning) based on ten independent variables. Constant (−4.168) indicates a low baseline probability of support when all variables are zero. X20 (−0.598) refers to difficulty communicating with students online or weak interaction in virtual environments. Its negative effect means that increased communication challenges reduce the likelihood of supporting e-learning. X28 (−0.145) represents a lack of institutional support or insufficient training for e-learning. Its slightly negative coefficient shows that limited training or technical support slightly lowers acceptance. X8 (+0.814) adherence to lecture schedules strongly increases the likelihood of support. X6 (+0.709) teaching suitability from home has a positive effect on support. X24 (+0.670) has a positive view of blended learning as a solution for crises, enhancing acceptance. X11 (+0.618) availability of lecture recordings raises the level of support. X18 (+0.586), the need for extra time for online teaching increases the probability of acceptance. X10 (+0.526) effective use of educational tools positively influences acceptance. X27 (+0.336) constructive feedback mechanisms slightly increase support. Summary: Higher values of (X8, X6, X24, X11, X18, X10, X27) increase faculty members' likelihood of supporting e-learning. In contrast, (X20 and X28, which reflect weak institutional support) slightly reduce that probability.

3. Conclusion and Recommendation

E-learning helps students and faculty to access learning materials anytime and anywhere. Also, reduces commuting and infrastructure costs and learning in remote areas. E-learning proved useful during the COVID-19 pandemic and similar situations. This study examined the key factors influencing Saudi university faculty members' acceptance of blended learning (e-learning) as an alternative to traditional education. Employing Decision Tree, Neural Network, and Logistic Regression analyses, the results consistently identified adherence to lecture schedules (X8), lecture recording (X11), teaching from home (X6), the need for extra time (X18), and perceiving blended learning as a solution during crises

(X24) are the strongest predictors of faculty support for e-learning. These findings underscore that technological readiness, time management, and positive attitudes toward blended learning play critical roles in promoting faculty acceptance. In contrast, challenges such as limited time for online exams (X20) and the nature of certain academic disciplines (X28) were associated with reduced acceptance, highlighting persistent contextual and structural barriers. After getting these results, we recommend:

- Systematic benchmarking of competencies against traditional leadership frameworks. First, identify the adaptable human-centric leadership that can co-create with technology and ethical AI use. Second, examine traditional leadership frameworks such as Servant Leadership and Transformational Leadership. Third, establish benchmarking criteria, identify overlaps, and highlight gaps. Finally, demonstrate how traditional skills evolve or expand as competencies develop.
- Higher education institutions must prioritize digital pedagogy and assessment design through semester-long faculty training programs. As the survey results indicate, these areas are key to improving online teaching effectiveness, as identified by faculty members.
- Enhance Institutional Support: Universities should provide continuous technical training and reliable digital infrastructure to strengthen faculty readiness for e-learning.
- Promote Time Flexibility: Institutions should address time-related barriers by designing schedules and workloads compatible with online teaching demands.
- Encourage Blended Learning Integration: Given its effectiveness during crises, blended learning should be institutionalized as a sustainable model beyond emergency contexts.
- Provide Incentives and Recognition: Rewarding innovative online teaching practices can increase faculty motivation and engagement.
- Future Research: Further studies could explore longitudinal data and student perspectives to validate these findings and assess the long-term impact of blended learning adoption. This means instead of studying faculty attitudes toward e-learning at one-point, longitudinal data would observe those situations over several semesters or years, showing how and why they evolve**.**

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