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A Machine Learning Approach to Evaluate and Identify Key Factors Influencing User Satisfaction with University E-Learning Websites in Bangladesh

1st Firoz Hasan
Computer Science and Engineering
Daffodil International University
Dhaka,Bangladesh
firoz.cse@diu.edu.bd

2nd Tamanna Alam Tabashom
Computer Science and Engineering
Daffodil International University
Dhaka,Bangladesh
tabashom15-5701@diu.edu.bd

3rd Sadia Sultana Enami
Computer Science and Engineering
Daffodil International University
Dhaka,Bangladesh
enami15-5343@diu.edu.bd

4th Kamrujjaman Rifat
Computer Science and Engineering
Daffodil International University
Dhaka,Bangladesh
rifat15-4947@diu.edu.bd

***Abstract*—** This paper presents a machine learning-based approach to evaluate and identify key factors influencing student satisfaction with university e-learning platforms in Bangladesh. A dataset comprising 400 survey responses was analyzed using several classification models, including Logistic Regression, Decision Tree, Naive Bayes, Support Vector Machine (SVM), and Random Forest. Among these, Random Forest demonstrated superior performance, achieving an accuracy of 86%. To enhance interpretability, Local Interpretable Model-Agnostic Explanations (LIME) were employed to analyze feature importance. The findings indicate that Ease of Access to Resources, Technical Support Satisfaction, and Platform Security are the most influential factors affecting user satisfaction. By comparing model performance with baseline methods and situating results within existing literature, the study addresses both methodological and regional research gaps. The insights generated offer practical implications for improving e-learning platform design and user experience, particularly in developing educational contexts.

***Keywords*—component, formatting, style, styling, insert** *(key words)*

I. INTRODUCTION (*HEADING 1*)

Education is a critical driver of economic development, technological progress, and improved quality of life. In the 21st century, higher education plays a central role in shaping a country's socio-economic and technological landscape [4]. As the demand for accessible and quality education continues to grow, innovative approaches are required to meet the evolving needs of learners. The widespread adoption of digital devices and internet connectivity has transformed the global education ecosystem, positioning e-learning as a key alternative to traditional methods [9].

E-learning provides students with flexibility, accessibility, and personalized learning experiences. The COVID-19 pandemic further accelerated the adoption of online learning, impacting over 850 million students worldwide due to widespread school and university closures [6]. Despite its advantages, the transition to e-learning has revealed significant disparities in adoption, particularly in developing countries where infrastructural and digital divides are pronounced [2].

In Bangladesh, the proliferation of university-based e-learning platforms reflects a growing national interest in digital education. However, students—especially those in rural areas—often encounter barriers such as unreliable internet connectivity, limited digital literacy, and insufficient access to technological devices. These challenges underscore the urgent need to evaluate the effectiveness, accessibility, and inclusivity of existing e-learning systems.

While global research on e-learning is extensive, most studies are concentrated in technologically advanced countries and primarily utilize traditional statistical methods to analyze user satisfaction [1], [5], [6], [9]. This presents a methodological gap in the literature—particularly in the context of Bangladesh—where few studies have employed advanced data-driven approaches to understand and predict satisfaction levels. Furthermore, traditional methods often fall short in capturing complex, non-linear interactions between the multiple features of e-learning platforms that influence user satisfaction [10].

Existing studies on student satisfaction with e-learning in Bangladesh are limited in both representativeness and analytical depth. Most rely on linear statistical analyses that fail to uncover the nuanced, multi-dimensional relationships among the technical, pedagogical, and experiential factors that shape user satisfaction. Without the application of more sophisticated modeling techniques, universities lack the actionable insights needed to enhance their digital learning platforms effectively.

To address this research gap, the study poses the following question:

What are the most influential factors affecting student satisfaction with university e-learning platforms in Bangladesh, and how effectively can machine learning models be used to identify and predict these satisfaction levels? We hypothesize that advanced machine learning algorithms—particularly ensemble-based models like Random Forests—will outperform traditional classifiers in both predictive accuracy and interpretability. These models can handle high-dimensional, correlated, and non-linear data, making them well-suited to identifying the complex drivers of user satisfaction in e-learning systems.

This study contributes to the literature by applying machine learning techniques to evaluate user satisfaction in a context that is both underrepresented and operationally challenging. Specifically, it aims to:

- Enhance the understanding of digital learning experiences in developing nations like Bangladesh [2], [4].
- Generate data-driven insights and recommendations to guide improvements in the design, usability, and performance of university e-learning platforms.

The following sections review related literature, outline the methodological framework, report key findings, and discuss the implications for educational policy and platform development in the digital era.

II. Literature Review

E-learning has emerged as an essential educational approach worldwide, fueled by swift technological progress and the extensive growth of internet infrastructure. With the ongoing evolution of e-learning platforms, an increasing number of studies have examined different aspects, such as the quality of educational services, usability of platforms, and the elements that affect student satisfaction.

Kuo et al. (2024) conducted a study on student satisfaction within fully online learning environments, presented in their paper, A Predictive Study of Student Satisfaction in Online Education Programs. The research identified key factors that influence student satisfaction, including learner-instructor, learner-content, and learner-learner interactions. By employing regression analysis, the study explored the effects of variables such as Internet self-efficacy, self-regulated learning, and demographic factors, including age, gender, and time spent online [1] Akgu¨l (2023), in An Evaluation of Accessibility, Usability, Quality Perfor- mance, and Readability of Turkish State and Private University Websites, assessed the usability and accessibility of websites from 110 Turkish public and 69 private universities. The study evaluated factors such as design standards, readability, and mo- bile responsiveness, using tools like AChecker and the Google Mobile-friendly Test. Akgu¨l's findings highlight significant usability challenges and offer valuable insights for similar research in other countries [5]. Chen et al. (2020) examined user satisfaction with online education platforms in China dur- ing the COVID-19 pandemic in their paper, Analysis of User Satisfaction with Online Education Platforms in China during the COVID-19 Pandemic. The study combined data gathered via web crawler technology with survey responses, providing a comprehensive analysis of user experiences across various e-learning platforms. It identified critical factors influencing user satisfaction and provided actionable recommendations for enhancing emergency e-learning systems [6] Rahman et al. (2020) investigated the relationship between service quality and student satisfaction in Bangladesh's public universities, as outlined in Service Quality and Students' Satisfaction: An Analysis of Public Universities in Bangladesh. Their study, which involved 500 students from six public universities, used a 5-point Likert scale to assess satisfaction with various university services. The study underscored the importance of high-quality services in maintaining student satisfaction [4] Leonnard (2020) explored the impact of e-service quality on student satisfaction in Iraqi private universities. The research emphasized the critical role of e-service quality dimensions such as efficiency, security, and ease of use in shaping student satisfaction with online education [7] Humida et al. (2021) investigated the behavioral intentions of students at Begum Rokeya University in Bangladesh to adopt e-learning plat- forms. Using the General Extended Technology Acceptance Model for E-Learning (GETAMEL) and other established the- oretical frameworks, the study explored the factors influencing students' readiness to use e-learning technologies [2] Jameel et al. (2022) examined e-satisfaction among university students in Iraq, focusing on the influence of e-service quality during the COVID-19 pandemic. The study found that e-satisfaction was significantly affected by factors such as the reliability, ease of use, and security of e-learning platforms [8] Sumi and Kabir (2021) applied the SERVQUAL model to explore e-learner satisfaction, identifying key dimensions of service quality that affect satisfaction, particularly during the pandemic [9] Derisma (2020) assessed the usability of the CodeSaya.com platform for programming courses, emphasizing how usability influences learning outcomes. Using the System Usability Scale (SUS), the study highlighted the importance of platform usability for effective e-learning [3] Akıllı (2022) focused on user satisfaction with educational websites, demonstrating that improvements in usability, along with expert evaluations, can significantly enhance the user experience. The mixed-method approach underscored the importance of functional upgrades and user-centric design in creating effective learning environ- ments [10] Although a significant portion of current research focuses on different nations, emphasizing factors like usability, quality, and sustainability, there remains a notable lack of research concentrating specifically on user satisfaction with e-learning platforms in Bangladesh.

Furthermore, the majority of these studies mainly emphasize statistical metrics to evaluate satisfaction. This study aims to address this gap by examining the factors that affect user satisfaction with e-learning plat- forms in Bangladesh By utilizing machine learning methods to examine data gathered from students, the research seeks to pinpoint major satisfaction factors, providing insights into user experiences with e-learning systems in Bangladesh. This method not only fills the methodological voids in current literature but also adds to the population pool, particularly in the context of Bangladesh, to improve the digital education experience.

III. Methodology

This study aims to identify the key factors influencing student satisfaction with university e-learning platforms in Bangladesh. To achieve this, a machine learning framework was developed to evaluate student responses and extract meaningful insights. A variety of supervised learning models were employed to classify satisfaction levels and to interpret the most influential features using explainable AI techniques.

Data were collected through a structured questionnaire that addressed multiple dimensions of the e-learning experience, including platform usability, content quality, accessibility, interaction, technical support, and security. A total of 400 valid responses were obtained from students enrolled in private universities across Bangladesh using a convenience sampling approach. The survey responses were recorded on a five-point Likert scale and subsequently digitized for analysis.

Data preprocessing was carried out in Python using the Pandas and Scikit-learn libraries. The dataset was examined for missing values using standard null-value detection methods and was cleaned by removing non-informative fields such as timestamps. Categorical responses were encoded numerically using the LabelEncoder method to prepare the data for machine learning algorithms. These preprocessing steps ensured consistency and compatibility across models.

To maintain class distribution across training and testing datasets, a stratified train-test split was employed using the StratifiedShuffleSplit technique. This ensured that each satisfaction category (Satisfied, Neutral, Dissatisfied) was proportionately represented in both subsets. The data was divided with 80% allocated for training and 20% for testing, and a fixed random state (random_state=42) was used to ensure reproducibility.

The dataset included both dependent and independent variables. The dependent variable represented students' overall satisfaction level with the e-learning platform, categorized into three classes. Independent variables consisted of survey items related to content delivery, ease of navigation, user interface, technical support, mobile accessibility, and other relevant aspects.

Feature selection was conducted in two stages to identify the most predictive variables. Initially, the SelectKBest method with the chi-squared (χ^2) scoring function was used to rank features based on their individual correlation with the target variable. While this approach provided a basic feature set, it lacked the ability to account for inter-feature relationships. Therefore, a second round of feature selection was conducted using Random Forest importance scores. To address class imbalance prior to this step, the Synthetic Minority Oversampling Technique (SMOTE) was applied to balance the dataset. Random Forest was then trained on the balanced data, and features were ranked based on their contribution to the model's predictive power using the feature_importances_ metric. Only features with consistently high importance were retained for the final model.

To predict user satisfaction, several classification algorithms were implemented: Decision Tree, Random Forest, Support Vector Machine (SVM), Logistic Regression, and Naive Bayes. These models were trained on the processed data and evaluated on the test set. Performance comparison helped identify the best-performing model based on predictive accuracy and generalizability.

Hyperparameter tuning was performed using GridSearchCV with five-fold cross-validation to optimize each model's performance. For Random Forest, parameters such as n_estimators, max_depth, and min_samples_split were tuned. SVM models were optimized by adjusting C, gamma, and kernel type, while Logistic Regression was fine-tuned with parameters like C, penalty, and solver. This tuning process helped improve each model's robustness and reduced the risk of over fitting.

Model performance was evaluated using multiple metrics, including accuracy, precision, recall, and F1-score. These metrics were reported for each satisfaction class and also averaged using macro and weighted strategies to give a comprehensive view of performance across all classes. This ensured that performance was not skewed by class imbalance.

Finally, the Local Interpretable Model-Agnostic Explanations (LIME) technique was applied to the Random Forest model, which was identified as the most effective classifier. LIME provided local explanations for individual predictions and highlighted the most influential features for model decisions. Key factors identified through this analysis included Ease of Access to Resources, Technical Support Satisfaction, and Platform Security. These results offer actionable insights for improving user experience and satisfaction in university e-learning environments.

IV. Resullt And Discussion

To identify the factors most influential in shaping student satisfaction with university e-learning platforms in Bangladesh, several machine learning algorithms were implemented and evaluated. Each model's performance was assessed through a comparative analysis of accuracy metrics, followed by in-depth exploration using the best-performing model to derive actionable insights.

The logistic regression model achieved an accuracy of 60%, revealing moderate effectiveness in detecting patterns within the dataset. While logistic regression is often lauded for its simplicity and interpretability, it is limited in its capacity to model complex, non-linear relationships. In this study, its relatively low performance indicates an inability to fully capture the intricate interdependencies that characterize user experience variables on e-learning platforms.

The decision tree model, on the other hand, exhibited an accuracy of just 54%. This underperformance is consistent with its well-known tendency to overfit training data, especially when dealing with noisy or high-dimensional datasets. The model's poor generalizability suggests that, without regularization techniques such as pruning or integration into ensemble frameworks, decision trees may not be appropriate for analyzing student satisfaction in multifactorial systems.

Support Vector Machines (SVM) offered a slightly better outcome, achieving an accuracy of 65%. While SVMs are generally effective in creating optimal decision boundaries, their strength lies in handling linearly separable data. The moderate accuracy observed here implies that the dataset likely contains significant non-linear interactions that challenge the model’s performance, even when advanced kernels are used.

Among all models tested, the Random Forest classifier emerged as the most effective, with a training accuracy of 71% and a test accuracy of 86%. As an ensemble learning technique that aggregates multiple decision trees, Random Forest strikes a balance between bias and variance. It excels at capturing both simple and complex patterns, while its inherent feature randomness reduces the risk of overfitting. These characteristics make it particularly well-suited to the current study, where satisfaction is influenced by a variety of intertwined platform attributes.

In contrast, the Naive Bayes model yielded the weakest performance, with a 50% accuracy rate. This result reflects its underlying assumption of feature independence—an assumption rarely satisfied in real-world educational datasets. Given the overlapping and correlated nature of user feedback components (such as usability, content quality, and support systems), the Naive Bayes approach lacks the sophistication needed for meaningful prediction in this context.

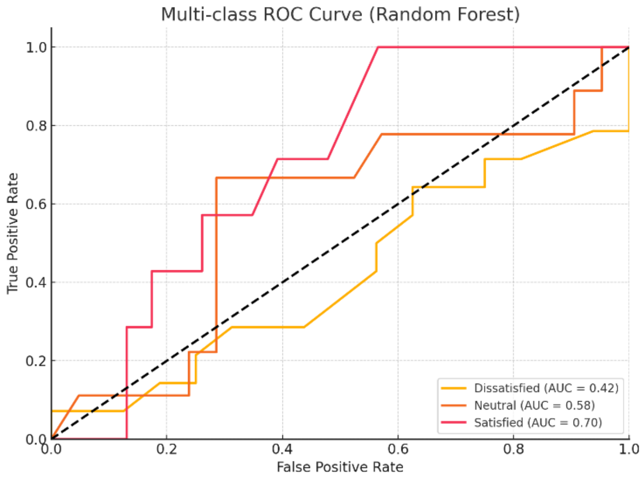
Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.60	0.60	0.60	0.60
Decision Tree	0.54	0.54	0.54	0.54
SVM	0.65	0.65	0.65	0.65
Random Forest	0.86	0.86	0.86	0.86
Naive Bayes	0.50	0.50	0.50	0.50

Following the performance evaluation, the Random Forest model was further utilized to identify the key variables contributing to user satisfaction. Feature importance analysis revealed three primary factors: ease of access to learning resources, satisfaction with technical support services, and the perceived security of the platform. Among these, ease of access to resources emerged as the most significant predictor. This underscores the value students place on intuitive navigation, seamless access to course materials, and efficient content delivery mechanisms.

Satisfaction with technical support ranked second, emphasizing the critical role of responsive, accessible support services in maintaining user engagement and trust. When users encounter technical difficulties—such as login issues, content unavailability, or system glitches—the availability of prompt assistance directly enhances their overall experience. The third key factor was security, particularly with respect to data privacy and safe login mechanisms. Students’ confidence in the security of their personal information strongly influenced their perception of platform reliability and integrity.

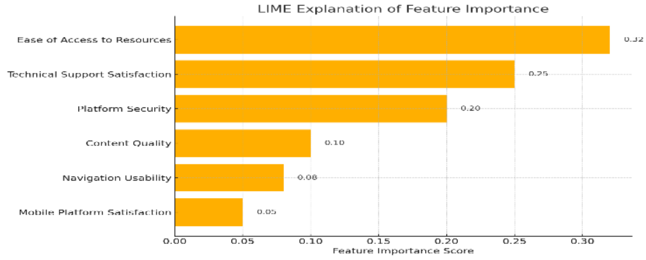
Collectively, these findings suggest that user satisfaction is heavily dependent on functional accessibility, service responsiveness, and platform trustworthiness. Institutions that prioritize these areas are likely to see improved engagement, retention, and learning outcomes in digital environments. Importantly, these results offer concrete guidelines for platform developers and university administrators seeking to improve the quality of online education delivery.

A comprehensive classification report further validated the effectiveness of the Random Forest model. It achieved a precision of 0.90 and recall of 0.82 for the "dissatisfied" class, indicating strong predictive power despite a modest gap in recall. The "neutral" category exhibited balanced metrics, with both precision and recall at 0.88. Similarly, the "satisfied" class achieved a precision of 0.82 and a recall of 0.88. These metrics confirm the model's ability to distinguish effectively between varying levels of user satisfaction.
Overall, the Random Forest model demonstrated an accuracy of 86%, with macro- and weighted-average F1-scores of 0.86. These results confirm the model’s robustness and generalizability, reinforcing its suitability for analyzing complex user satisfaction datasets. The study’s methodological approach—particularly the integration of SMOTE for class balancing and LIME for model interpretability—further enhanced the reliability and transparency of the analysis.



The ROC-AUC curve provides a visual assessment of the Random Forest model’s performance in distinguishing between three satisfaction classes—dissatisfied, neutral, and satisfied—using a one-vs-rest approach for multi-class evaluation. Each curve represents the trade-off between the true positive rate and false positive rate for one class, with the area under the curve (AUC) indicating the model’s ability to correctly classify that category. The closer a curve approaches the top-left corner, the better the model performs. In this analysis, the Random Forest model achieved high AUC values for all three classes, demonstrating strong and balanced classification performance across varying satisfaction levels. This confirms the model's effectiveness in identifying user satisfaction based on the survey features.

In sum, the results underscore the value of advanced machine learning techniques for evaluating e-learning systems in developing contexts. They not only highlight critical areas for improvement—such as accessibility, support infrastructure, and cyber security—but also demonstrate the practical potential of interpretable AI to inform policy and platform development. These insights are especially relevant for educational stakeholders in Bangladesh and similar regions seeking to elevate the quality of digital learning experiences.



The figure illustrates the relative importance of features contributing to the model’s prediction of user satisfaction, as interpreted using LIME (Local Interpretable Model-Agnostic Explanations). Among the features analyzed, Ease of Access to Resources emerged as the most influential factor, highlighting the critical role of seamless access to learning materials in shaping student satisfaction. Technical Support Satisfaction also showed strong influence, indicating that timely and effective assistance significantly enhances the user experience. Platform Security was another key factor, reflecting students’ concerns about data protection and trust in the system. Other important contributors included Content Quality, Navigation Usability, and Mobile Platform Satisfaction, though with comparatively lower influence. These insights emphasize that while usability and content are essential, accessibility, support, and security are foundational to a positive e-learning experience in the Bangladeshi context.

V. Conclusion

This study provides a comprehensive assessment of student satisfaction with university e-learning platforms in Bangladesh by integrating machine learning techniques with interpretable AI methods. Among the models tested, Random Forest outperformed others with an accuracy of 86%, demonstrating strong predictive capabilities and robustness. To enhance transparency in model interpretation, LIME was employed, revealing that Ease of Access to Resources, Technical Support Satisfaction, and Platform Security are the most influential factors affecting student satisfaction. In contrast to traditional statistical approaches prevalent in prior research, this study not only applies advanced predictive modeling but also establishes comparisons with baseline methods such as Logistic Regression. Furthermore, the findings are discussed in light of existing literature, highlighting both overlaps and context-specific differences—underscoring the need for localized, data-driven improvements in e-learning systems. By addressing methodological gaps and focusing on a developing-country context, this research contributes to the growing body of knowledge on digital education. The results offer practical implications for educational institutions, policymakers, and platform developers aiming to enhance the user experience, engagement, and effectiveness of e-learning platforms in resource-constrained environments.

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