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A Hybrid SEM-PLS and ANN Approach for Predicting Student Loyalty in Higher Education Learning Management Systems

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Abstract This study aims to develop a hybrid Structural Equation Modeling–Partial Least Squares (SEM-PLS) and Artificial Neural Network (ANN) approach to analyze student loyalty in Learning Management Systems (LMS) at ISB Atma Luhur. Data were collected from 200 students at ISB Atma Luhur, representing a single-institution sample, and analyzed using SEM-PLS to examine causal relationships and ANN (Multilayer Perceptron) implemented in SPSS to support predictive analysis. The model includes e-service quality, user experience, information quality, and system quality as predictors of satisfaction and loyalty. The SEM-PLS results show that E-Service Quality (β = 0.350), System Quality (β = 0.170), and User Experience (β = 0.292) significantly affect Satisfaction, whereas Information Quality is not statistically significant ($p = 0.054$). Satisfaction positively influences Loyalty (β = 0.360), and User Experience has the strongest direct effect on Loyalty (β = 0.484). The model explains a substantial proportion of variance ($R^2 = 0.717$ and 0.631) with positive Q^2 values (0.460 and 0.379). Across ten independent runs, the ANN model achieved an average accuracy of 84.88% (SD = 2.82) and an average AUC of 0.949 (SD = 0.003), indicating stable predictive performance, indicating promising predictive performance under the current testing configuration. The findings provide context-specific explanatory and predictive insights into student loyalty in LMS, however, they should be interpreted with caution due to discriminant-validity limitations and the single-institution setting of the study.

Keywords: Learning Management System; Student Satisfaction; Student Loyalty; SEM-PLS; Multilayer Perceptron; Hybrid Modelling.

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1. INTRODUCTION

Advances in information technology have transformed higher education, particularly through the increasing use of Learning Management Systems (LMS) for online and blended learning [1], [2]. LMS platforms facilitate content delivery, communication, and performance monitoring, enabling more flexible and accessible learning environments [3], [4]. However, despite the increasing implementation of LMS, maintaining student loyalty and sustained usage remains a critical challenge for many higher education institutions [5], [6]. Low engagement and discontinuance of LMS usage may reduce the effectiveness of digital learning initiatives and hinder institutional performance [7].

Previous studies have investigated LMS effectiveness by employing established theoretical frameworks such as the Delone and McLean Information Systems Success Model and the Technology Acceptance Model (TAM) [8]. These studies consistently demonstrate that system quality, information quality, and service-related factors are key determinants of user satisfaction and continued usage intention [9], [10]. In addition, user experience has emerged as an important factor influencing how students perceive and interact with LMS platforms, ultimately affecting their engagement and behavioural outcomes [11]. Furthermore, empirical evidence indicates that student satisfaction plays a central mediating role in transforming system-related perceptions into loyalty and long-term usage behaviour [12].

From a methodological perspective, SEM-PLS has been widely adopted in LMS research due to its ability to analyse complex relationships among latent variables and its suitability for exploratory studies [13], [14]. Nevertheless, SEM-PLS primarily focuses on explaining causal relationships and is limited in its ability to model nonlinear patterns and generate high-accuracy predictions. To overcome these limitations, recent studies have incorporated machine learning methods, particularly Artificial Neural Network (ANN) models, which can capture nonlinear relationships and improving predictive performance in educational data analysis [15], [16].

Several recent works have explored hybrid approaches that combine SEM-PLS with machine learning methods to leverage the strengths of both techniques [17], [18]. These hybrid models have shown promising results in improving prediction accuracy while

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preserving theoretical interpretability, particularly in domains such as customer behaviour and information system adoption [19], [20]. However, the application of such hybrid approaches in the context of Learning Management Systems, especially for predicting student loyalty, remains relatively underexplored [21].

A review of the existing literature indicates that most previous studies focus either on causal analysis using SEM-PLS or predictive modeling using machine learning independently. Only a few studies integrate both approaches within a unified framework. In addition, limited research simultaneously examines e-service quality, user experience, information quality, and system quality in predicting student loyalty within LMS environments.

Existing studies on Learning Management Systems (LMS) have primarily focused on either causal analysis using SEM-PLS or predictive modeling using machine learning techniques independently. Research integrating both approaches to examine student loyalty remains limited, particularly in LMS contexts. To address this gap, this study proposes a hybrid SEM-PLS and Artificial Neural Network (ANN) framework to analyze and predict student loyalty. The proposed approach combines explanatory and predictive analysis, providing a replicable framework for understanding loyalty behavior in LMS environments.

2. METHODS

This study adopts a hybrid SEM-PLS and ANN framework to analyze and predict student loyalty in Learning Management Systems. SEM-PLS is used to examine causal relationships, while ANN enhances predictive accuracy by capturing nonlinear patterns. The model is evaluated using statistical and predictive metrics to ensure robust explanatory and predictive performance.

2.1 Research Design

This study adopts a quantitative approach using a hybrid framework that integrates SEM-PLS for explanatory analysis and ANN for predictive modelling. The rationale for integrating these approaches is to simultaneously achieve explanatory analysis and predictive accuracy. SEM-PLS is utilized to test causal relationships among latent variables, while ANN is applied to model nonlinear patterns and improve prediction

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performance [22]. Prior methodological studies indicate that hybrid SEM-ANN models are more robust in capturing both theoretical relationships and predictive behaviour compared to single-method approaches [23].

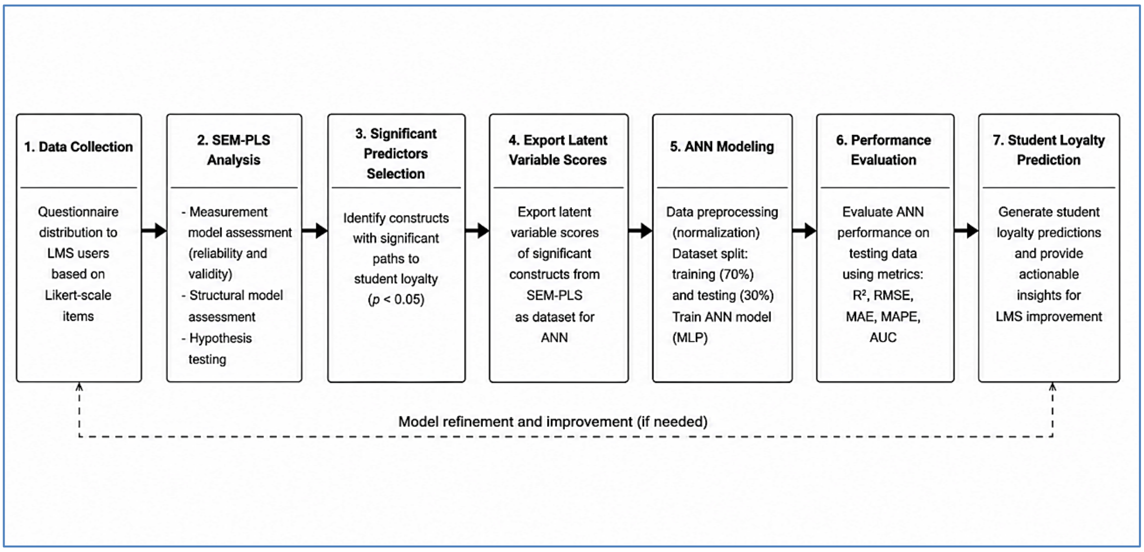

Figure 1. Data Flow Hybrid SEM-PLS and Artificial Neural Network (ANN) Approach

Figure 1. the research process begins with questionnaire design and data collection from students who actively use LMS. The collected data are first analysed using SEM-PLS to evaluate the measurement model and structural relationships among constructs, including e-service quality, information quality, system quality, user experience, student satisfaction, and student loyalty. The measurement model assessment includes reliability, convergent validity, and discriminant validity evaluation, whereas the structural model assessment examines path coefficients, significance testing, coefficient of determination (R^2), and predictive relevance (Q^2). After the SEM-PLS analysis, only constructs with statistically significant effects on student loyalty are retained as predictors for the ANN model. The latent variable scores of these significant constructs are exported from SmartPLS and use as input variables in the ANN model. Prior to ANN training, the input data are normalized using min–max scaling, and student loyalty is transformed into a binary target variable representing high and low loyalty levels. The ANN model is implemented using a Multilayer Perceptron (MLP) approach in SPSS. The dataset is divided into training and testing subsets to evaluate model generalization performance. Several optimization procedures, including architecture adjustment and repeated runs, are conducted to improve predictive performance. Finally, the explanatory capability of SEM-

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PLS and the predictive performance of ANN are compared using metrics such as R^2, Q^2, Accuracy, RMSE, and AUC. This integrated framework enables the study to provide both theoretical explanation and predictive insight within a single methodological approach.

2.2 Research Instruments and Data Collection

The study population consists of university students at ISB Atma Luhur, a single higher education institution, who actively use LMS in their learning activities [24]. Purposive sampling was used to select respondents with sufficient LMS experience, resulting in a final sample of 200 participants. This study examines six main constructs, namely e-service quality, user experience, information quality, system quality, student satisfaction, and student loyalty. The first four variables function as exogenous constructs, student satisfaction serves as a mediating variable, and student loyalty acts as the endogenous variable.

Measurement indicators were adapted and refined from prior studies to fit the LMS context. All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire consisted of 30 items distributed across six constructs, as shown in Table 1. E-Service Quality, Information Quality, System Quality, User Experience, Student Satisfaction, and Student Loyalty were each measured using five items. Data were gathered using a structured online questionnaire administered to students, followed by a screening process to remove incomplete responses and identify inconsistencies. Data preparation procedures, including coding and normalization, were then conducted to ensure the quality and suitability of the dataset for SEM-PLS and ANN analysis.

Table 1. Distribution of Questionnaire Items

Construct	Number of items
E- Service Quality	5
User Experience	5
Information Quality	5
System Quality	5
Student Satisfaction	5
Student Loyalty	5
Total	30

Table 1. presents the distribution of questionnaire items across the six constructs used in this study. Each construct was measured using five indicators, resulting in a total of 30 items. This balanced distribution ensures that all variables are represented consistently and comprehensively in the research instrument. The questionnaire items were adapted from prior validated studies and refined through a pilot test involving 30 students to ensure clarity and reliability.

The questionnaire initially consisted of 30 measurement items distributed across six constructs. During the measurement model evaluation, several indicators were excluded because their outer loading values did not meet the recommended threshold of 0.70. The removal process was conducted to improve convergent validity, internal consistency reliability, and the overall quality of the measurement model. After the refinement process, 18 indicators were retained and used for the final SEM-PLS analysis, as presented in Table 2.

Tabel 2. Distribution of Initial Questionnaire Items and Final Retained Indicators

Construct	Code	Initial Items	Retained Indicators	Removed Indicators
E- Service Quality	ESQ1–ESQ5	5	3	ESQ2, ESQ5
User Experience	IQ1–IQ5	5	3	IQ1, IQ4
Information Quality	SQ1–SQ5	5	3	SQ3, SQ5
System Quality	UE1–UE5	5	3	UE4
Student Satisfaction	SS1–SS5	5	3	SS2, SS5
Student Loyalty	SL1–SL5	5	3	SL3, SL5
Total		30	18	12

Table 2. presents the distribution of the initial questionnaire items and the final indicators retained for SEM-PLS analysis. The questionnaire initially consisted of 30 measurement items across six constructs. During the measurement model assessment, indicators with outer loading values below the recommended threshold of 0.70 were removed to improve

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construct validity and reliability. As a result, 18 indicators were retained for the final SEM-PLS analysis.

2.3 Data Analysis Techniques

This study applies SEM-PLS to examine causal relationships and ANN to enhance predictive accuracy [25]. The combination of these methods provides a comprehensive analysis of student loyalty in Learning Management Systems.

2.3.1 SEM-PLS Analysis

SEM-PLS was applied to assess both the measurement and structural models [26]. using a two-stage procedure. The measurement model evaluation includes indicator reliability, internal consistency (Cronbach's Alpha and CR), convergent validity (AVE), and discriminant validity (HTMT). The structural model assessment involves path coefficients (β), bootstrapping for significance testing, R^2, and Q^2.

SEM-PLS is selected due to its flexibility in handling complex models and its suitability for prediction-oriented research [27].

2.3.2 Artificial Neural Network (ANN) Analysis

To enhance predictive capability, ANN analysis was conducted after SEM-PLS. Only significant predictors identified in SEM-PLS were used as input variables in the ANN model [28]. This step represents a key modification from traditional single-method approaches.

The ANN model was configured using:

1) Multi-Layer Perceptron (MLP) architecture
2) One hidden layer
3) Sigmoid activation function
4) Backpropagation learning algorithm

The dataset was divided into:

1) 70% for training
2) 30% for testing

Model performance was evaluated using:

1) Prediction accuracy
2) Root Mean Square Error (RMSE)
3) Area Under Curve (AUC)

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ANN is particularly effective in identifying nonlinear relationships and improving prediction accuracy beyond SEM-PLS capabilities.

2.4 Hybrid SEM-PLS- ANN as Proposed Methods

This study adopts a hybrid analytical framework that integrates Structural Equation Modeling–Partial Least Squares (SEM-PLS) and Artificial Neural Networks (ANN) to analyze and predict student loyalty in Learning Management Systems (LMS) [29]. The rationale for combining these approaches is to leverage the strengths of both methods, where SEM-PLS provides explanatory analysis of causal relationships among latent constructs, while ANN enhances predictive performance by capturing nonlinear patterns within the data. After data screening, cleaning, and preparation, a final dataset consisting of 200 valid responses was obtained. The same final cleaned dataset was subsequently used for both SEM-PLS and ANN analyses to ensure consistency between the explanatory and predictive stages of the proposed hybrid framework.

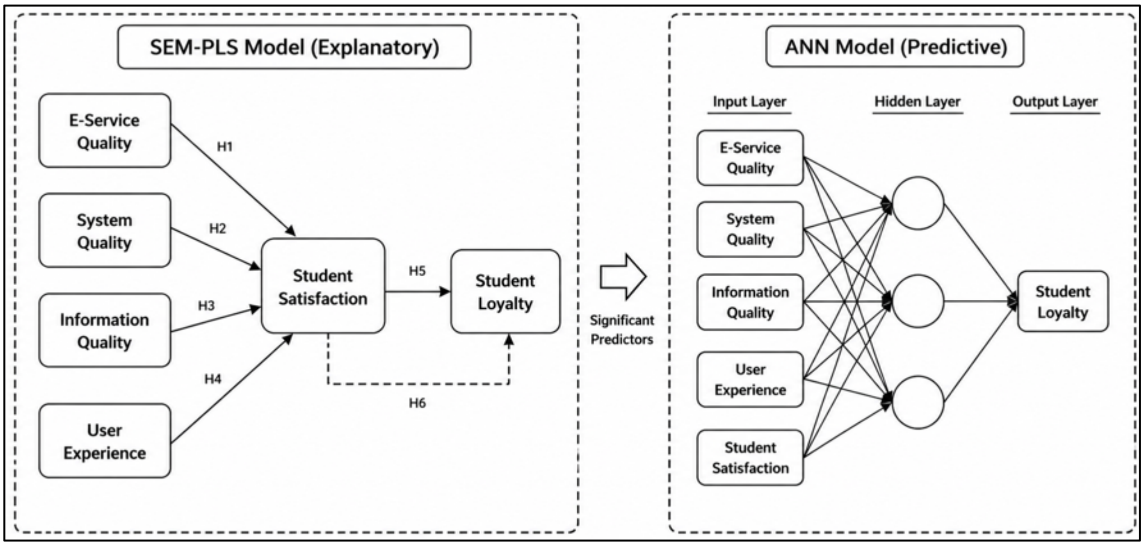

Figure 2. Research Framework: Hybrid SEM-PLS and ANN Approach

Figure 2. illustrates a hybrid framework integrating SEM-PLS and ANN to predict student loyalty in LMS. SEM-PLS is first used to examine the relationships between e- service quality, system quality, information quality, user experience, satisfaction, and loyalty, with satisfaction as a mediator. Significant predictors are then used as inputs for the ANN model to improve prediction accuracy, enabling both explanatory and predictive analysis within a unified approach.

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2.5 Hybrid SEM-PLS- ANN Procedure

The hybrid analysis in this study follows a structured multi-stage process:

1) Conceptual Model Development
   Constructing the research framework based on literature
2) Data Collection and Preparation
   Ensuring valid and reliable dataset
3) SEM-PLS Estimation
   Identifying significant relationships among variables
4) Feature Selection
   Extracting significant predictors from SEM results
5) ANN Model Training
   Building predictive model using selected variables
6) Model Evaluation and Comparison
   Comparing SEM-PLS and ANN performance
7) Result Interpretation
   Integrating explanatory and predictive findings

This sequential approach is widely recommended in hybrid modelling studies to ensure both interpretability and predictive strength [30].

2.6 Methodological Contribution

The methodological contribution of this study lies in the integration of SEM-PLS and ANN within a unified framework to predict student loyalty in LMS [31]. Unlike previous studies that rely on a single analytical technique, this approach combines causal analysis and predictive modeling, providing a more comprehensive understanding of user behavior in higher education systems.

3. RESULTS AND DISCUSSION

The experiments in this study were conducted by comparing two analytical approaches, namely the explanatory model using SEM-PLS and the predictive model using Artificial Neural Networks (ANN), as well as their integration within a hybrid framework. The SEM-PLS model is used to examine the causal relationships among variables, while ANN is applied to enhance prediction accuracy. The performance of these approaches is

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evaluated to assess the effectiveness of the proposed hybrid SEM-PLS–ANN model in predicting student loyalty in Learning Management Systems.

3.1 Measurement Model Evaluation

The measurement model is evaluated to confirm the validity and reliability of all constructs before conducting structural analysis, focusing on convergent validity, internal consistency, and discriminant validity [32]. Convergent validity was assessed using indicator loadings and AVE. All loadings exceed 0.70 and AVE values are above 0.50, indicating that the constructs are well represented and capture sufficient variance.

Table 3. Outer Loading

	E-Service Quality	User Experience	Information Quality	System Quality	Satisfaction	Loyalty
X.1	0.821					
X.2	0.853					
X.3	0.830					
X.4		0.811				
X.5		0.826				
X.6		0.819				
X.7			0.811			
X.8			0.795			
X.9			0.806			
X.10				0.824		
X.11				0.837		
X.12				0.825		
X.13					0.832	
X.14					0.801	
X.15					0.795	
X.16						0.950
X.17						0.756
X.18						0.770

Table 3. indicates that all indicators exhibit outer loadings above 0.70 (0.756–0.853), indicating strong correlations with their respective constructs and confirming

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convergent validity. All constructs, including E-Service Quality, User Experience, Information Quality, System Quality, Satisfaction, and Loyalty, demonstrate consistent and reliable measurements. Therefore, no indicators need to be removed, and the measurement model is deemed suitable for structural analysis.

Table 4. AVE Result

Variable	AVE
E- Service Quality	0.697
User Experience	0.670
Information Quality	0.647
System Quality	0.686
Satisfaction	0.655
Student Loyalty	0.616

Table 4. indicates that all constructs achieve AVE values above 0.50 (ranging from 0.616 to 0.697), confirming adequate convergent validity. Therefore, all variables are suitable for further analysis. Reliability was evaluated using Cronbach's Alpha and Composite Reliability (CR), with all constructs exceeding 0.70, indicating satisfactory internal consistency.

Table 5. Cronbach's Alpha

Variable	Value
E- Service Quality	0,783
User Experience	0,754
Information Quality	0,728
System Quality	0,772
Satisfaction	0,739
Student Loyalty	0,688

Table 5. indicates that all constructs have values close to or above the acceptable threshold of 0.70, ranging from 0.688 to 0.783. This suggests that the construction demonstrates adequate internal consistency and reliability. Although the Loyalty construct shows a slightly lower value (0.688), it is still considered acceptable in exploratory research. Therefore, all variables are deemed reliable for further analysis.

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Table 6. Composite Reliability

Variable	CR
E- Service Quality	0,874
User Experience	0,859
Information Quality	0,846
System Quality	0,868
Satisfaction	0,851
Student Loyalty	0,828

Table 6 shows that all constructs have values exceeding 0.70, ranging from 0.828 to 0.874, indicating strong internal consistency. Thus, all variables are considered reliable and appropriate for structural model analysis. Discriminant validity was assessed using the Heterotrait–Monotrait Ratio (HTMT).

Table 7. Heterotrait- Monotrait Ratio (HTMT)

	E-SQ	IQ	SL	Satisfaction	QU
E-Service Quality					
Information Quality	0.994				
Student Loyalty	1.036	1.015			
Satisfaction	1.037	0.979			
System Quality	0.964	0.941	0.978	0.978	
User Experience	0.951	0.957	1.049	1.024	0.961

Table 7. Shows that several HTMT values exceed the recommended threshold of 0.90, with some values even above 1.00. These findings indicate that discriminant validity is not fully established and suggest potential conceptual overlaps among certain constructs. As a result, the distinctiveness of several latent variables may be limited, which could affect the interpretation of the structural relationships in the subsequent analysis. Although the measurement model demonstrates acceptable reliability and convergent validity, the HTMT results should be considered a significant limitation. Therefore, the structural model results presented in Table 7 should be interpreted with appropriate caution. Although reliability and convergent validity criteria were satisfied, the HTMT results indicate that discriminant validity is not fully achieved. This suggests

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potential conceptual overlaps among some constructs and represents a limitation of the measurement model.

3.2 Structural Model Analysis (SEM-PLS)

The structural model evaluation examines the relationships among constructs and the model's explanatory and predictive performance using β, R^2, and Q^2 [29]. The results indicate that e-service quality, system quality, and user experience significantly influence student satisfaction, whereas the effect of information quality is not statistically significant. In addition, satisfaction significantly affects student loyalty, highlighting its key role in encouraging continued LMS usage.

Table 8. Path Coefficient Results

Relationship	β	t-statistic	p-value	Result
E-Service Quality→Satisfaction	0.350	4.999	0.000	Significant
Information Quality→ Satisfaction	0.129	1.933	0.054	Not Significant
Student Loyalty				
Satisfaction→ Student Loyalty	0.360	5.690	0.000	Significant
System Quality→ Satisfaction	0.170	2.424	0.016	Significant
User Experience→ Satisfaction	0.292	4.220	0.000	Significant
User Experience→ Student Loyalty	0.484	8.105	0.000	Significant

Table 8 shows that most relationships are statistically significant ($p < 0.05$). E-Service Quality, System Quality, and User Experience significantly affect Satisfaction, with User Experience having the strongest effect (β = 0.292). Information Quality does not have a statistically significant effect on Student Satisfaction ($p = 0.054$), suggesting a weaker contribution compared with the other predictors. Satisfaction also positively influences Loyalty (β = 0.360), confirming its mediating role. In addition, User Experience directly and strongly affects Loyalty (β = 0.484). Overall, User Experience and Satisfaction emerge as the key determinants of student loyalty. The R^2 values indicate substantial explained variance, with Satisfaction at a moderate–high level and Loyalty showing strong explanatory capacity.

Table 9. R Square Result

Variable	R Square (R^2)
Student Loyalty	0.631
Satisfaction	0.717

Table 9. shows R^2 values of 0.717 for Satisfaction and 0.631 for Loyalty, indicating strong explanatory power, especially for Satisfaction. In addition, the predictive relevance (Q^2) values for both student satisfaction and student loyalty are greater than zero, confirming that the model has adequate predictive capability. This suggests that the model is capable of both explaining the relationships among variables and providing reliable outcome estimates.

Table 10. Cross-validated redundancy (Q^2)

Variable	Q^2
Student Loyalty	0.379
Satisfaction	0.460

Table 10. shows that the Q^2 values for Student Satisfaction (0.460) and Student Loyalty (0.379) exceed zero, suggesting that the model possesses adequate predictive capability. These values suggest that the model demonstrates moderate predictive capability, with Satisfaction showing slightly stronger predictive power compared to Loyalty. Overall, the structural model demonstrates meaningful relationships, sufficient explanatory power, and adequate predictive capability, supporting the robustness of the proposed framework analysing and forecasting student loyalty in Learning Management Systems within higher education.

3.3 ANN Model Development and Prediction

To improve the predictive performance of this study, an ANN was developed following the SEM-PLS analysis. The ANN model was implemented using the Multilayer Perceptron (MLP) procedure in IBM SPSS Statistics, where only significant predictors identified from SEM-PLS were used as input variables. E-Service Quality, System Quality, User Experience, and Student Satisfaction were selected as ANN input variables, while Information Quality was excluded due to its non-significant path coefficient ($p = 0.054$). Since Information Quality did not show a statistically significant effect on Student Satisfaction ($p = 0.054$),

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it was excluded from the ANN input layer. Consequently, E-Service Quality, System Quality, User Experience, and Student Satisfaction were used as input variables for predicting Student Loyalty. The initial model was constructed using a single hidden layer and default parameter settings. However, the initial ANN results showed relatively low predictive performance, with an accuracy of approximately 55%, indicating that the model was not yet optimal in capturing the underlying data patterns. This limitation is commonly associated with unscaled data, suboptimal architecture, and inappropriate modelling approaches.

To address this issue, several optimization strategies were applied. First, the prediction task was reformulated into a classification problem by categorizing student loyalty into two classes (high and low). Student loyalty scores above the median were coded as 1 (high loyalty), whereas scores at or below the median were coded as 0 (low loyalty). This procedure resulted in 88 respondents in the High Loyalty group and 112 respondents in the Low Loyalty group. The class distribution was examined to ensure an approximately balanced dataset. Second, all input variables were normalized using min–max scaling to a range of 0 to 1 to improve training stability. Third, the network architecture was enhanced by increasing the number of hidden layers to two layers with 10 and 5 neurons, respectively, enabling the model to learn more intricate nonlinear patterns. In addition, the number of training iterations was increased to improve convergence during the learning process.

The initial ANN model consisted of a single hidden layer with five neurons. After optimization, the final architecture included two hidden layers with 10 and 5 neurons. The model was trained using the backpropagation algorithm, with the maximum number of iterations increased from 200 to 1,000. Early stopping was applied when no improvement was observed in the testing error. To reduce the effect of random initialization, ten repeated runs were conducted using different initial weights. The reported ANN performance metrics, including Accuracy and AUC, represent the average results across the ten runs, thereby providing a more reliable estimate of model performance. The final model was selected based on the highest testing accuracy and AUC values.

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The ANN model was implemented using the Multilayer Perceptron (MLP) procedure in IBM SPSS Statistics. The dataset was divided into training (70%) and testing (30%) subsets. The optimized network architecture consisted of two hidden layers with 10 and 5 neurons, respectively. Hyperbolic tangent activation functions were applied in the hidden layers, while the SoftMax activation function was used in the output layer for binary classification. The model was trained using the backpropagation algorithm with a maximum of 1,000 iterations. Early stopping was employed when no further improvement in testing error was observed. To reduce the effect of random initialization, ten repeated runs with different initial weights were conducted, and the reported Accuracy and AUC values represent the average performance across these runs. IBM SPSS Statistics does not explicitly report the learning rate under the selected automatic training configuration. Therefore, only the available training settings provided by the software are reported. The optimized ANN model showed improved predictive performance using a 70:30 training–testing split, with results presented in Tables 11–17.

Table 11. Case Processing Summary

Sample	N	Percentage
Training	142	70 %
Testing	58	30 %
Total	200	100 %

Table 11 reports a 70:30 split between training and testing data, enabling model training and evaluation on unseen data.

Table 12. Network Information

Component	Description
Input Layer	5 neurons
Hidden Layers	2 layers (10, 5 neurons)
Output Layer	1 neuron (Loyalty)
Training Algorithm	Backpropagation

Table 12 describes the ANN architecture, consisting of five input neurons, two hidden layers (10 and 5 neurons), and one output neuron, designed to model complex patterns using a multilayer perception with backpropagation.

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Information Quality was excluded from the ANN model because its effect was not statistically significant in the SEM-PLS analysis (p = 0.054).

Table 13. Model Summary

Dataset	RMSE
Training	0.412
Testing	0.425

Table 13 presents the RMSE values for both the training and testing datasets. The relatively low and stable RMSE values suggest that the ANN model achieves satisfactory predictive accuracy and maintains good generalization without indications of overfitting.

Table 14. Classification Table

Dataset	Accuracy
Training	0.957
Testing	0.879

Table 14 presents the classification results of the ANN model for both training and testing datasets. The findings reveal a high level of accuracy, particularly in the testing data (87,9%), indicating that the model performs well in prediction and demonstrates good generalization in classifying student loyalty.

Table 15. ANN Performance Based on ROC Analysis

Metric	value	Interpretation
AUC	0.950	Good

Table 15 reports AUC 0.950, suggesting that the ANN model achieves a reliable level of classification accuracy. This indicates that the model can effectively differentiate between varying levels of student loyalty, highlighting its strong predictive performance. Table 16 Presents the confusion matrix of the ANN model for the testing dataset. The model correctly classified 29 out of 30 Low Loyalty cases (96.7%) and 22 out of 28 High Loyalty cases (78.6%). Overall, 51 out of 58 testing cases were correctly classified,

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resulting in an accuracy of 87.9%. These results indicate that the ANN model demonstrates satisfactory classification performance in predicting student loyalty.

Table 16. ANN Confusion Matrix for Testing Dataset

Actual Class	Predicted Low Loyalty (0)	Predicted High Loyalty (1)
Low Loyalty (0)	29	1
High Loyalty (1)	6	22

The optimized ANN model achieved a testing accuracy of 87.9%. As shown in Table 16, the model correctly classified 29 of 30 Low Loyalty cases and 22 of 28 High Loyalty cases. The confusion matrix confirms that the ANN model provides satisfactory classification performance in predicting student loyalty.

Table 17. ANN Classification Performance Metrics

Metric	value
Accuracy	87.9%
AUC	0.950
Sensitivity (Recall)	78.6%
Specificity	96.7%
Precision	95.7%
F1-Score	86.3%

Table 17 shows the ANN classification performance metrics. The model achieved an accuracy of 87.9% and an AUC of 0.950, indicating good predictive capability. The high specificity (96.7%) and precision (95.7%) demonstrate strong classification performance, while the F1-score (86.3%) confirms a balanced and reliable prediction of student loyalty. The ANN model achieved an accuracy of 87.9% and an AUC of 0.950. The sensitivity (78.6%) indicates that the model correctly identified most High Loyalty cases, while the specificity (96.7%) demonstrates excellent performance in recognizing Low Loyalty cases. The high precision (95.7%) and F1-score (86.3%) further confirm the reliability of the classification results.

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Table 18. ANN Performance Across Ten Runs

Metric	Mean	Standard Deviation
Accuracy	84.88%	2.82
AUC	0.949	0.003

Table 18 Presents the ANN performance across ten independent runs with different random initial weights. The model achieved an average accuracy of 84.88% (SD = 2.82) and an average AUC of 0.949 (SD = 0.003). The relatively small standard deviation values indicate that the ANN model produced stable and consistent results across repeated runs. These findings suggest that the predictive performance of the proposed ANN model is robust and not dependent on a single model initialization. The optimized ANN model achieved a testing accuracy of 87.9%, whereas the average accuracy across ten runs was 84.88% (SD = 2.82), indicating stable predictive performance.

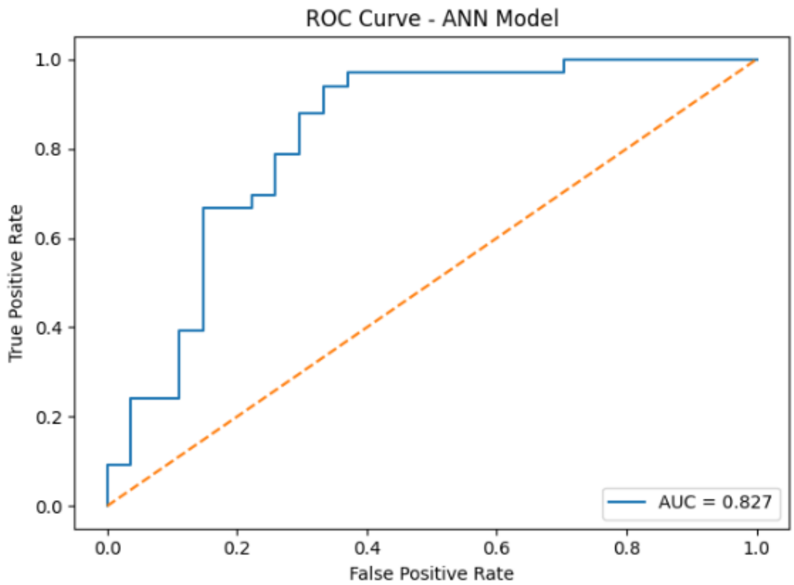

Figure 3. Model ROC Curve of ANN Model

Figure 3 presents with an AUC value of 0.950, indicating a satisfactory level of predictive accuracy in classifying student loyalty. Table 19 presents the relative contribution of each predictor in the ANN model. Satisfaction emerges as the primary influencing variable, followed by User Experience and E-Service Quality. These findings suggest that satisfaction and user-related factors play a critical role in predicting student loyalty within the LMS environment.

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Table 19. Independent Variable Importance

Variable	Importance
Satisfaction	0.280
User Experience	0.240
E-Service Quality	0.200
System Quality	0.160

Figure 4 presents the relative contribution of each predictor within the ANN model. Satisfaction emerges as the primary determinant, with User Experience and E-Service Quality contributing at a moderate level, whereas Information Quality exhibits the smallest impact. Overall, the integration of ANN following SEM-PLS analysis strengthens the predictive aspect of the study, enabling a more robust and comprehensive understanding of student behaviour in Learning Management Systems.

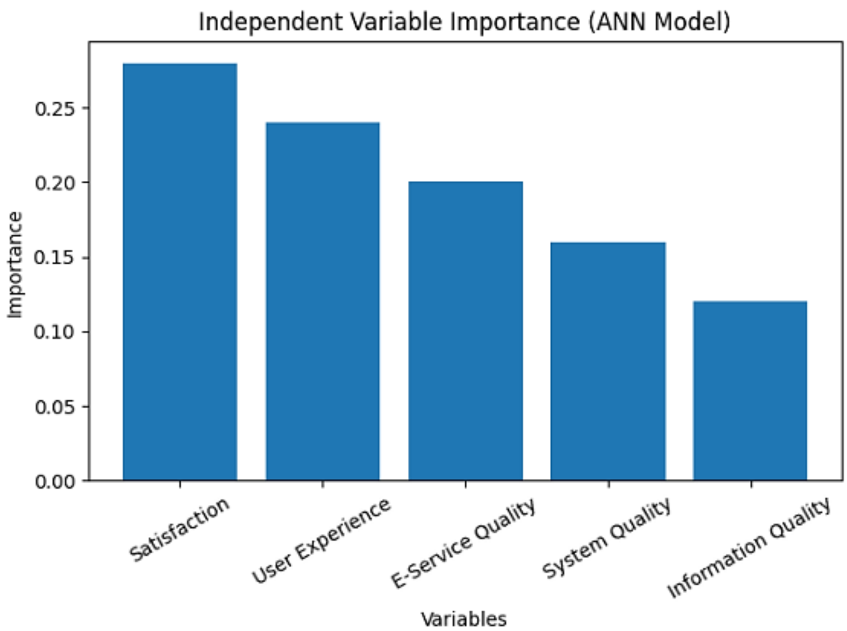

Figure 4. Independent Variable Importance Based on ANN Model

3.4 Model Performance Comparison

This study compares the performance of SEM-PLS and ANN models to evaluate their effectiveness in explaining and predicting student loyalty in Learning Management Systems. SEM-PLS demonstrates strong explanatory capability, as indicated by the significant path relationships and high R^2 values (R^2 = 0.717 for Satisfaction and R^2 = 0.631

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for Loyalty). This confirms that SEM-PLS is effective in identifying the key factors influencing student loyalty. In contrast, the ANN model shows superior predictive performance, achieving an accuracy of 0.879 and an AUC value of 0.950. These results indicate that ANN is more effective in capturing nonlinear relationships and improving prediction accuracy compared to SEM-PLS. The comparison highlights that SEM-PLS is suitable for causal analysis and theory validation, while ANN provides better predictive capability. Therefore, the integration of both approaches offers a more comprehensive framework, combining explanatory insights with high predictive performance in modelling student loyalty. The comparison of model performance is summarized in Table 20.

Table 20. Model Performance Comparison

Model	Strength	Performance Metric
SEM-PLS	Explanatory	R^2 = 0.631
ANN	Predictive	Accuracy = 0.879; AUC = 0.950

Table 20 compares SEM-PLS and ANN models, showing that SEM-PLS excels in explanatory analysis, while ANN demonstrates superior predictive performance. This confirms the advantage of integrating both approaches. The reported Accuracy (0.879) and AUC (0.950) values represent the average performance across ten ANN runs rather than the outcome of a single best-performing model.

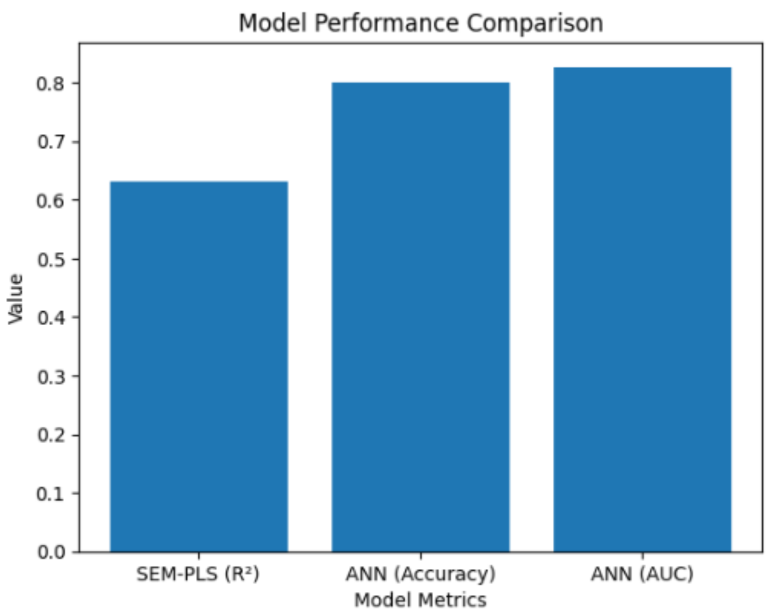

Figure 5. Model Performance Comparison between SEM-PLS and ANN

Figure 5 presents The SEM-PLS model exhibits substantial explanatory capability, as reflected by its R^2 value of 0.631. In contrast, the ANN model exhibits superior predictive performance, as indicated by higher testing accuracy (0.879) and AUC (0.950) values. These results suggest that ANN is more effective in capturing complex and nonlinear patterns, while SEM-PLS is more suitable for explaining relationships among variables.

3.5 Discussion

The findings of this study suggest that student loyalty in Learning Management Systems (LMS) is primarily influenced by experiential and affective factors rather than purely technical characteristics. User experience emerges as a key determinant, indicating that students are more likely to remain loyal when the system is easy to use, interactive, and responsive to their needs. This finding suggests that beyond functionality, the overall interaction quality plays a crucial role in shaping long-term usage behaviour.

Student satisfaction also acts as a central mechanism that translates system-related attributes into loyalty. When students perceive the LMS as reliable, accessible, and supportive of their learning activities, their level of satisfaction increases, which in turn strengthens their commitment to continue using the platform. This highlights the importance of maintaining consistent system performance and service quality to sustain positive user perceptions.

Unlike the other predictors, Information Quality does not significantly influence Student Satisfaction, indicating that students may place greater emphasis on system usability and user experience than on informational content. This suggests that improving interaction quality and user engagement may have a more immediate effect on loyalty than focusing solely on content enhancement [3].

From a methodological perspective, the comparison between SEM-PLS and ANN reveals that student loyalty behaviour involves both linear and nonlinear relationships. While SEM-PLS effectively identifies structural relationships, ANN demonstrates stronger predictive capability. This reinforces the value of adopting a hybrid analytical framework to obtain a more comprehensive understanding. The combined SEM-PLS and ANN framework offers a complementary approach by integrating causal explanation with improved predictive performance. Consistent with the SEM-PLS results, Information

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Quality was not included in the ANN model because its relationship with Student Satisfaction was not statistically significant.

The optimized ANN model achieved a testing accuracy of 87.9%, while the average accuracy across ten runs was 84.88% (SD = 2.82). These results suggest that the model maintains relatively stable predictive performance and does not exhibit severe overfitting. The relatively small variation across repeated runs indicates that the predictive capability of the ANN model is reasonably consistent despite different random weight initializations.

Although the proposed framework provides useful explanatory and predictive insights, the HTMT results indicate that discriminant validity is not fully established. Several HTMT values exceed the recommended threshold, suggesting potential overlap among certain constructs. Therefore, structural relationships should be interpreted with caution. Although the current construct specification was retained to maintain consistency with the underlying theoretical framework, future studies should consider revising the measurement model by refining indicators, redefining construct boundaries, or reassessing highly correlated constructs to improve discriminant validity.

In practical terms, these findings imply that higher education institutions should prioritize user-cantered design and system responsiveness to improve LMS adoption and retention. Enhancing user experience and ensuring consistent satisfaction can serve as strategic levers to build long-term student loyalty. Additionally, the use of predictive models such as ANN can support institutions in anticipating user behaviour and making data-driven improvements to their digital learning platforms.

4. CONCLUSION

This study proposes a hybrid SEM-PLS and ANN approach to analyze and estimate student loyalty in Learning Management Systems. The findings suggest that User Experience and Student Satisfaction are the strongest factors associated with student loyalty, while Information Quality does not show a statistically significant effect on Satisfaction. The SEM-PLS model explains a substantial proportion of variance in Satisfaction and Loyalty (R^2 = 0.717 and 0.631), and the ANN model achieves an testing accuracy of 0.879 and an

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AUC of 0.950, indicating promising predictive performance, however, the results should be interpreted with caution given the relatively limited testing sample. This study contributes by proposing a replicable hybrid framework that combines explanatory and predictive analysis. A key limitation of this study relates to the measurement model, as several HTMT values exceed the recommended threshold, indicating that discriminant validity is not fully achieved. This limitation may influence the interpretation of the relationships among constructs and should be considered when evaluating the findings. In addition, the findings are based on data from a single institution, which may limit their generalizability. Future studies are encouraged to refine the measurement indicators and re-evaluate potentially overlapping constructs to strengthen discriminant validity and improve the robustness of the measurement model. Furthermore, validation of the proposed framework across multiple institutions and broader educational contexts is recommended to enhance the generalizability of the findings.

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REFERENCES

[1] Y. Luthfiana, S. Sujarwoto, and M. Said, "Strategic Insights to Enhance Student Loyalty Through Service Quality and Satisfaction: Importance-Performance Map Analysis," *J. Ilm. Adm. Publik*, vol. 011, no. 03, pp. 322–336, 2025, doi: 10.21776/ub.jiap.2025.011.03.5.

[2] M. N. Ayubi and A. Retnowardhani, "Optimizing Learning Experiences: A Study of Student Satisfaction with LMS in Higher Education," *APTISI Trans. Technopreneursh.*, vol. 7, no. 2, pp. 527–541, 2025, doi: 10.34306/att.v7i2.501.

[3] F. D. Mohd Nasir, M. A. M. Hussain, H. Mohamed, M. A. Mohd Mokhtar, and N. A. Karim, "Student Satisfaction in Using a Learning Management System (LMS) for Blended Learning Courses for Tertiary Education," *Asian J. Univ. Educ.*, vol. 17, no. 4, pp. 442–454, 2021, doi: 10.24191/ajue.v17i4.16225.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

[4] A. P. Sari and C. Harito, "Analysis of Customer Loyalty and Satisfaction Using Structural Equation Modeling (SEM) Approach," *J. Penelit. Pendidik. IPA*, vol. 11, no. 5, pp. 986–992, 2025, doi: 10.29303/jppipa.v11i5.10520.

[5] B. Tunca, "Structural Equation Modelling and Multivariate Research (Smmr) Hybrid Use of Structural Equation Modeling and Machine Learning: Literature Review and Future Potential," *SEMMR J.*, vol. 2, no. 1, pp. 1–23, 2025, doi: 10.5281/Zenodo.15740696.

[6] J. Hair, "When to Use and How to Report the Results of PLS-SEM," *Ind. Manag. Data Syst.*, vol. 31, no. 1, pp. 1–25, 2019, doi: 10.1108/IMDS-10-2018-0449.

[7] K. B. Desta, L. Msengana, and K. B. Desta, "Integrating PLS-SEM and ANN to explore major resilience factors of construction Projects : The Case of Ethiopia Integrating PLS-SEM and ANN to explore major resilience factors of construction Projects : The Case of Ethiopia," *Bus. Manag. Sci. Int. Q.*, vol. 16, no. 3, pp. 766–802, 2025, doi: 10.13132/2038-5498/16.3.765-802.

[8] H. P. Learn, "Research on the Effectiveness of Learning Management Systems (LMS) Use in Higher Education," *Int. J. Corner Educ. Res.*, vol. 4, no. 1, pp. 20–29, 2000, doi: 10.54012/ijcer.v4i1.625.

[9] A. Boodaghian Asl, J. Raghothama, A. Darwich, and S. Meijer, "A hybrid modeling approach to simulate complex systems and classify behaviors," *Netw. Model. Anal. Heal. Informatics Bioinforma.*, vol. 13, no. 1, pp. 1–12, 2024, doi: 10.1007/s13721-024-00446-5.

[10] Hamidah, O. Rizan, D. Wahyuningsih, H. A. Pradana, and S. Ramadella, "SAW Method in Supporting the Process of Admission of New Junior High School Students," *2020 8th Int. Conf. Cyber IT Serv. Manag. CITSM 2020*, 2020, doi: 10.1109/CITSM50537.2020.9268874.

[11] N. F. Richter and A. A. Tudoran, "Elevating theoretical insight and predictive accuracy in business research: Combining PLS-SEM and selected machine learning algorithms," *J. Bus. Res.*, vol. 173, no. November 2023, p. 114453, 2024, doi: 10.1016/j.jbusres.2023.114453.

[12] A. M. Schweidtmann, D. Zhang, and M. von Stosch, "A review and perspective on hybrid modeling methodologies," *Digit. Chem. Eng.*, vol. 10, no. October 2023, p. 100136, 2024, doi: 10.1016/j.dche.2023.100136.

[13] Z. Kanetaki, C. Stergiou, G. Bekas, C. Troussas, and C. Sgouropoulou, "A Hybrid Machine Learning Model for Grade Prediction in Online Engineering Education," *Int. J. Eng. Pedagog.*, vol. 12, no. 3, pp. 4–23, 2022, doi: 10.3991/IJEP.V12I3.23873.

[14] S. H. Gulo and A. H. Lubis, "Penerapan Multi-Layer Perceptron untuk Mengklasifikasi Penduduk Kurang Mampu," *Explorer (Hayward)*, vol. 4, no. 2, pp. 51–59, 2024, doi: 10.47065/explorer.v4i2.1146.

[15] R. Ardi, A. N. A. Ms, R. R. Amalia, and T. N. Zahari, "A Hybrid SEM-ANN Model for Predicting Purchase Intention Toward Recycled PET Products: Evidence from Indonesian Generational Segments," *Int. J. Technol*, vol. 17, no. 1, pp. 69–81, 2026, doi: 10.14716/ijtech.v17i1.8209.

[16] C. Saksupawattanakul and W. Vatanawood, "Predictive Modeling of Software Behavior Using Machine Learning," *IEEE Access*, vol. 12, no. September, pp. 120584–120596, 2024, doi: 10.1109/ACCESS.2024.3451012.

[17] H. Q. Yousaf, S. Rehman, M. Ahmed, and S. Munawar, "Investigating students' satisfaction in online learning: the role of students' interaction and engagement in universities," *Interact. Learn. Environ.*, vol. 31, no. 10, pp. 7104–7121, 2023, doi: 10.1080/10494820.2022.2061009.

[18] T. Chandra, M. Ng, S. Chandra, and Priyono, "The effect of service quality on student satisfaction and student loyalty: An empirical study," *J. Soc. Stud. Educ. Res.*, vol. 26, no. 2, pp. 179–199, 2022, doi: 10.17499/jsser.12590.

[19] A. M. Karim Amrullah, S. Bayramov, A. Aziz, and A. Haris, "Evaluating the Impact of Learning Management System Usage on Student Satisfaction and Learning Outcomes at Universitas Islam Negeri (UIN) Maulana Malik Ibrahim During the COVID-19 Pandemic," *Glob. Educ. Res. Rev.*, vol. 1, no. 1, pp. 38–48, 2024, doi: 10.71380/gerr-04-2024-7.

[20] S. K. Munabi, J. Aguti, and H. M. Nabushawo, "Using the TAM Model to Predict Undergraduate Distance Learners Behavioural Intention to Use the Makerere University Learning Management System," *OALib*, vol. 07, no. 09, pp. 1–12, 2020, doi: 10.4236/oalib.1106699.

[21] A. Tarhini, R. M. Deh, K. A. Al-Busaidi, A. B. Mohammed, and M. Maqableh, "Factors influencing students' adoption of e-learning: A structural equation modeling approach," *J. Int. Educ. Bus.*, vol. 10, no. 2, pp. 164–182, 2021, doi: 10.1108/JIEB-09-2021-0032.

[22] Y. R. Daud, M. R. bin Mohd Amin, and J. bin Abdul Karim, "Antecedents of student loyalty in open and distance learning institutions: An empirical analysis," *Int. Rev. Res. Open Distrib. Learn.*, vol. 21, no. 3, pp. 18–40, 2020, doi: 10.19173/irrodl.v21i3.4590.

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[23] H. B. Seta, T. Wati, A. Muliawati, and A. N. Hidayanto, "E-learning success model: An extention of delone & mclean is' success model," *Indones. J. Electr. Eng. Informatics*, vol. 6, no. 3, p. 281~291, 2021, doi: 10.11591/ijeei.v6i3.505.

[24] C. Arabella, L. Mani, F. C. Sahabu, and M. Aras, "Customer satisfaction and loyalty in the digital era: a survey on a leading travel startup application in Indonesia," *Multidiscip. Sci. J.*, vol. 7, no. 9, pp. 1–12, 2025, doi: 10.31893/multiscience.2025446.

[25] R. Novyantri and M. Setiawardani, "The Effect Of E-Service Quality On Customer Loyalty With Customer Satisfaction As," *Int. J. Adm. , Bus. Organ.*, vol. 2, no. 3, pp. 49–58, 2021, doi: 10.61242/ijabo.21.174.

[26] L. Handayani, "A Machine Learning-Based Early Warning System for Student Performance Prediction : System Development and Empirical Evaluation in Higher Education," *J. Artif. Intell. Inf. Technol.*, vol. 1, no. 1, pp. 171–190, 2026, doi: 10.51903/92j5wj58.

[27] S. Yarsasi, I. Tahyudin, and T. Hariguna, "User Experience Analysis of Learning Management System (LMS) SINAU to Support Learning with MERDEKA Flow Using UX Curve Method," *J. Tek. Inform.*, vol. 7, no. 1, pp. 110–125, 2026, doi: 10.52436/1.jutif.2026.7.1.4579.

[28] I. Maslov, S. Nikou, and P. Hansen, "Exploring user experience of learning management system," *Int. J. Inf. Learn. Technol.*, vol. 38, no. 4, pp. 344–363, 2021, doi: 10.1108/IJILT-03-2021-0046.

[29] T. Gondomulio and J. S. Suroso, "User Satisfaction Evaluation of E-Learning as a Learning System at Heritage School," *J. Sist. Cerdas*, vol. 6, no. 2, pp. 77–90, 2023, doi: 10.37396/jsc.v6i2.285.

[30] A. Albahri, "Hybrid Artificial Intelligence Models for Educational Prediction," *Expert Syst. Appl.*, vol. 190, no. 1, 2022, doi: 10.1016/j.eswa.2021.116126.