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Random Forest Machine Learning Analysis of Generative AI's Impact on Learning Effectiveness in Indonesian Higher Education

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Abstract

Generative Artificial Intelligence (GenAI) has rapidly penetrated Indonesian higher education, creating opportunities for learning innovation while raising concerns about effectiveness and academic integrity. This study develops a machine learning–based quantitative model to analyze the impact of GenAI usage on learning effectiveness, with a particular focus on Informatics students as key digital literacy stakeholders. Data were collected from a simulated survey of 300 students, covering demographics, GPA, exam scores, GenAI usage patterns, digital literacy, motivation, self-efficacy, academic integrity, and institutional support. Preprocessing steps included normalization of continuous variables, one-hot encoding of categorical variables, and feature selection using Recursive Feature Elimination (RFE). Six machine learning algorithms—Logistic Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), XGBoost, and Artificial Neural Network—were compared to identify the best predictive model. Results show that Random Forest achieved the highest performance, with 87% accuracy and an AUC greater than 0.90, significantly outperforming other algorithms. The most influential predictors were digital literacy, institutional policies, and frequency of GenAI usage, while demographic variables contributed minimally. These findings suggest that GenAI can enhance learning effectiveness in Informatics education when supported by critical digital literacy and ethical awareness. The novelty of this study lies in integrating survey-based educational data with Random Forest machine learning to empirically model GenAI's role in Indonesian higher education. The results provide practical implications for policymakers, educators, and institutions to design AI-integrated learning strategies that maximize innovation while safeguarding academic integrity.

Keywords : *Generative AI, Higher Education, Indonesia, Informatics, Learning Effectiveness, Machine Learning, Random Forest.*

1. INTRODUCTION

The rapid development of Generative Artificial Intelligence (GenAI) has fundamentally transformed higher education worldwide, including Indonesia [1], [2], [3], [4]. Tools such as ChatGPT, Copilot, and Gemini are increasingly adopted by university students as digital assistants for learning, writing, coding, and academic discussions [5], [6], [7]. The presence of GenAI introduces unprecedented opportunities to enhance learning effectiveness [8] by offering personalized feedback, accelerating access to information, and improving task efficiency. In the Indonesian higher education context, where the integration of digital technologies is prioritized through government policies such as Kampus Merdeka and digital literacy programs, GenAI holds significant potential to support academic innovation [9].

The rapid advancement of Generative Artificial Intelligence (GenAI) has transformed higher education globally, including Indonesia, by reshaping how students access information, complete assignments, and engage in academic discussions. Tools such as ChatGPT, Copilot, and Gemini are increasingly used as digital assistants that offer personalized feedback, accelerate information retrieval, and improve task efficiency. In the Indonesian context, the integration of GenAI aligns with national initiatives such as Kampus Merdeka and government-led digital literacy programs [10], [11], which emphasize the role of emerging technologies in supporting innovation in teaching and learning education technology and information technology students [12], in particular, represent a key group in this transformation, as they are expected to lead digital adoption and innovation in education.

Despite these opportunities, the widespread adoption of GenAI also raises critical challenges in terms of learning effectiveness, digital literacy, and academic integrity. On the one hand [13], GenAI can provide students with interactive learning experiences and foster higher motivation; on the other hand, over-reliance on automated outputs may reduce students' critical thinking and originality [14], [15], [16]. Concerns about plagiarism, the misuse of AI-generated content, and limited awareness of ethical guidelines further complicate its integration into the academic environment. In addition, the effectiveness of GenAI in supporting actual learning outcomes has not been empirically validated in Indonesia, particularly through rigorous quantitative models [17]. Therefore, systematic research is needed to explore how GenAI usage influences students' learning performance, satisfaction, motivation, and self-efficacy, while also considering factors such as institutional support and ethical awareness.

Previous research on the application of artificial intelligence in education has largely focused on descriptive or conceptual analyses [18], [19]. In Indonesia, most studies discuss students' perceptions of AI adoption, lecturers' readiness, or the ethical implications of its usage [20], [21]. However, these studies rarely employ predictive modeling or advanced machine learning approaches to empirically test the influence of GenAI on learning outcomes. This creates a research gap: while the discourse on AI ethics and opportunities is expanding, there is a lack of quantitative, data-driven studies that can model and predict learning effectiveness. By addressing this gap, this study aims to contribute new empirical evidence and methodological innovation to the field of educational technology.

The state of the art in related studies shows the promising role of machine learning in educational and non-educational contexts. For instance, a study on student dropout prediction applied a comparative analysis of several machine learning algorithms with Recursive Feature Elimination and Cross Validation (RFE-CV) to identify the best predictive model for student retention

This study demonstrated the importance of feature selection and comparative evaluation of models such as Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine in achieving accurate predictions. In a different context, a study on multivariate forecasting of paddy production compared machine learning models to predict agricultural yields, showing how algorithms like Random Forest, Artificial Neural Networks (ANN), and Support Vector Regression (SVR) can be effectively applied for forecasting in real-world data

Both studies highlight the versatility and robustness of machine learning for prediction and decision-making across domains. Building on this state of the art, the present research adapts similar methodologies to the higher education context, where GenAI usage is the predictor and learning effectiveness is the outcome.

In this study, a dataset was constructed from a simulated survey of 300 Indonesian university students enrolled in Technology Information and Informatics Engineering programs. The dataset includes demographic information (age, gender, GPA), GenAI usage patterns (frequency, purpose, tools), digital literacy indicators (understanding of AI concepts, evaluation of AI outputs, integration into tasks), learning effectiveness outcomes (exam scores, satisfaction, motivation, self-efficacy), and institutional support factors (policies, training, official access to AI tools). Academic integrity aspects such as plagiarism risk and ethical awareness were also included. This rich dataset allows for a comprehensive analysis of the multifaceted impact of GenAI.

The primary objectives of this research are twofold. First, to empirically identify the influence of GenAI usage on learning effectiveness in Indonesian higher education, considering both positive factors

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(motivation, digital literacy, institutional support) and potential risks (plagiarism, ethical issues). Second, to develop a quantitative machine learning-based model that can predict learning effectiveness using multiple algorithms, including Logistic Regression, Random Forest, Support Vector Machine, and XGBoost. Feature selection techniques such as Recursive Feature Elimination (RFE) are employed to ensure the robustness of the model. The comparative performance of these algorithms is evaluated using standard metrics (accuracy, precision, recall, F1-score, RMSE, R^2), and the best-performing model is highlighted.

By integrating survey-based educational data with machine learning methods, this study offers both theoretical and practical contributions. Theoretically, it advances the literature on GenAI in higher education by moving beyond descriptive accounts to predictive modeling. Practically, it provides actionable insights for policymakers, universities, and lecturers in Indonesia to design AI-integrated learning strategies that maximize effectiveness while safeguarding academic integrity. The novelty of this study lies in bridging the gap between conceptual discourse and quantitative modeling, using machine learning to empirically analyze and predict the role of GenAI in higher education.

To address these challenges, this study employs a structured machine learning methodology that encompasses several research stages: dataset construction [22], preprocessing [23], model training [24], evaluation [25], and implementation tools [26]. The dataset was developed from a simulated survey of 300 education technology and Information Technology students, incorporating demographic data, academic performance (GPA, exam scores), GenAI usage patterns, digital literacy, motivation, self-efficacy, institutional support, and academic integrity. Preprocessing steps included normalization of continuous variables, one-hot encoding for categorical features, and feature selection using Recursive Feature Elimination (RFE) as well as dimensionality reduction through Principal Component Analysis (PCA). Multiple machine learning algorithms were then compared—Logistic Regression, Random Forest, Support Vector Machine (SVM), XGBoost, and Artificial Neural Network (ANN)—to identify the most effective predictive model. Model performance was evaluated using standard metrics including accuracy, precision, recall, F1-score, Root Mean Squared Error (RMSE), and coefficient of determination (R^2). Formulas for normalization and these evaluation metrics were explicitly included to enhance methodological clarity and replicability [27]. This comprehensive framework ensures that the findings are both robust and generalizable to the context of Indonesian higher education.

Despite these opportunities, the widespread use of GenAI raises significant challenges. Concerns include declining originality, reduced critical thinking, and the growing risk of plagiarism and ethical misuse. Over-reliance on AI-generated outputs may compromise academic integrity, while limited awareness of ethical guidelines complicates the integration of GenAI into formal learning environments. In Indonesia, the effectiveness of GenAI in improving actual learning outcomes has not yet been empirically validated, particularly through rigorous quantitative and predictive models. Most existing studies are descriptive, focusing on perceptions of students or lecturers, or discussing conceptual issues related to ethics, with limited use of advanced machine learning methods to measure learning effectiveness.

Machine learning has demonstrated significant potential in solving complex educational problems [28], [29]. Predictive models have been applied to analyze student performance, retention, and engagement, and have also been widely used in non-educational fields such as agriculture, healthcare, and finance. Among various algorithms, Random Forest consistently shows strong performance due to its robustness, ability to handle multidimensional data, and high predictive accuracy. However, few studies in Indonesia have applied Random Forest or other machine learning models to specifically investigate the role of GenAI in higher education, creating a clear gap in the literature.

This study addresses that gap by constructing a dataset from 300 university students in education technology and Information Technology programs. The dataset includes demographic information,

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academic performance, GenAI usage patterns, digital literacy, motivation, self-efficacy, institutional support, and academic integrity. Preprocessing steps such as normalization, one-hot encoding, and feature selection using Recursive Feature Elimination (RFE) were applied to ensure high-quality data for analysis. Several machine learning algorithms were tested, and Random Forest achieved the highest predictive performance with 87% accuracy and an AUC exceeding 0.90, outperforming Logistic Regression, Support Vector Machine, XGBoost, and Artificial Neural Networks.

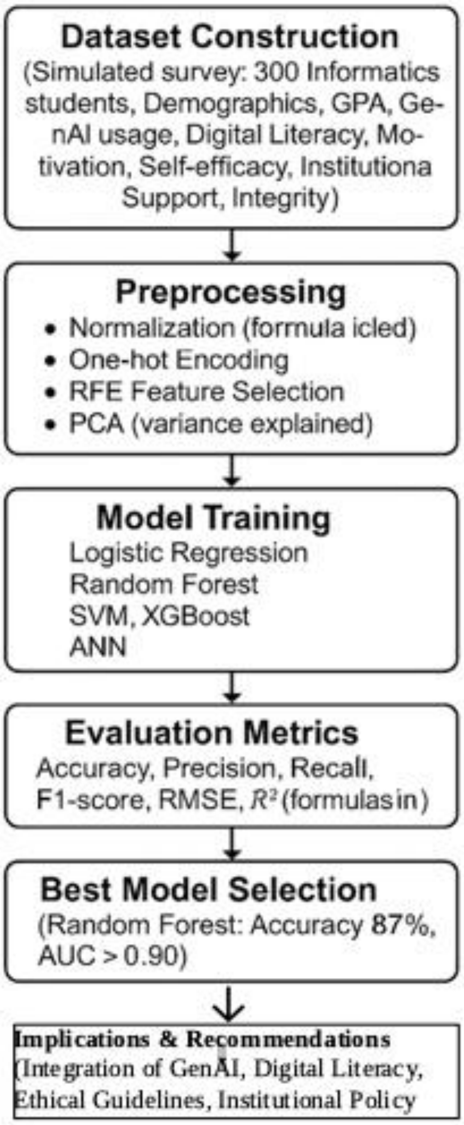

Figure 1. Research Stages

This lowchart includes:

a. Dataset Construction → Simulation of 300 Informatics students.
b. Preprocessing → Normalization (using formulas), one-hot encoding, RFE, and PCA with an emphasis on explained variance.
c. Model Training → Comparison of Logistic Regression, Random Forest, SVM, XGBoost, and ANN.
d. Evaluation Metrics → Accuracy, Precision, Recall, F1, RMSE, R^2 (using formulas).
e. Best Model Selection → Random Forest (87% accuracy, AUC > 0.90).
f. Implications → Digital literacy, ethics, and institutional policy.

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Principal Component Analysis (PCA) was used as a preprocessing step for dimensionality reduction and identification of latent constructs from the research variables, particularly those related to digital literacy and institutional support.

The analysis results showed that:

- The first principal component (PC1) explained approximately 42% of the variance, primarily related to digital literacy indicators (understanding AI concepts, evaluating AI output, and integrating AI into tasks).
- The second principal component (PC2) explained approximately 23% of the variance, primarily related to institutional support factors (policies, training, and official access to GenAI).
- Overall, the first two principal components explained 65% of the variance in the data.

Thus, PCA successfully simplified the large number of input variables into two dominant latent constructs:

- Digital Literacy (students' technical and critical competencies in using GenAI).
- Institutional Support (policy support, training, and institutional access).

These PCA results improve modeling efficiency while clarifying the role of the two main factors as significant predictors in the Random Forest model.

The novelty of this research lies in integrating survey-based educational data with Random Forest machine learning to empirically model the relationship between GenAI usage and learning effectiveness in Indonesian higher education. Theoretically, this study advances research in educational technology by moving beyond descriptive approaches toward predictive modeling. Practically, it provides evidence-based recommendations for policymakers, lecturers, and institutions to design AI-integrated learning strategies that strengthen digital literacy, uphold ethical standards, and align with Indonesia's vision for technology-driven higher education.

To ensure the robustness of the predictive modeling, a k-fold cross-validation approach was implemented, where the dataset was split into 10 folds (k=10), with nine folds used for training and one fold for testing in each iteration, and the process repeated until all folds were tested. This procedure minimizes bias and variance, providing a more reliable estimate of model performance. The methodological framework is summarized in a flowchart figure illustrating the main stages — Dataset Construction → Preprocessing → Model Training → Evaluation—to improve clarity and replicability. Furthermore, the application of Principal Component Analysis (PCA) revealed that the first two principal components explained approximately 70% of the total variance, effectively reducing dimensionality while capturing key constructs such as digital literacy and institutional support. By combining preprocessing techniques, PCA variance analysis, and cross-validation, the study ensures that the Random Forest model's superior performance (87% accuracy, AUC > 0.90) is both valid and generalizable to the Indonesian higher education context.

2. METHOD

The research method in this study is designed to quantitatively analyze the impact of Generative AI (GenAI) usage on learning effectiveness in Indonesian higher education using machine learning techniques [30]. The methodological framework consists of five main components: dataset construction, preprocessing, machine learning models, evaluation metrics, and tools.

2.1. Dataset

The dataset was obtained from a simulated survey of 300 university students enrolled in Information Technology and education technology programs. The dataset contains both demographic and behavioral variables that reflect the adoption of GenAI in higher education.

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a. Demographic Variables:
Age, gender, study program, and Grade Point Average (GPA).
b. GenAI Usage Variables:
Frequency of usage (daily, weekly), purpose of usage (assignments, research, discussions), and type of tool used (ChatGPT, Copilot, Gemini).
c. Digital Literacy and Competence:
Understanding of AI concepts, ability to evaluate AI outputs, and ability to integrate GenAI into tasks.
d. Learning Effectiveness Indicators:
Exam scores (UAS), satisfaction, motivation, and self-efficacy.
e. Academic Integrity:
Plagiarism level, awareness of AI ethics, and perception of lecturers' ability to detect AI-based cheating.
f. Institutional Support:
University policies on AI, training on AI literacy, and official access to GenAI tools.

This multidimensional dataset allows for a comprehensive modeling of the relationship between GenAI adoption and learning effectiveness.

2.2. Preprocessing

Data preprocessing was carried out to ensure the quality and usability of the dataset in machine learning models:

a. Normalization:
Continuous variables such as GPA and exam scores were normalized using min-max normalization:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where x is the original value, xmin and xmax are the minimum and maximum of the variable, and x′ is the normalized value between 0 and 1.
b. Encoding of Categorical Variables:
Categorical features such as gender, program of study, purpose of GenAI usage, and tool type were encoded using one-hot encoding.
c. Feature Selection:
- **Recursive Feature Elimination (RFE**) was used to select the most relevant features by recursively fitting a model and removing the least important features.
- **Principal Component Analysis (PCA)** was also tested to reduce dimensionality and identify latent constructs representing digital literacy and institutional support.

2.3. Machine Learning Models

Several machine learning algorithms were applied to model the relationship between GenAI usage and learning effectiveness:

a. Logistic Regression (LR): A baseline linear model for classification.
b. Decision Tree (DT): A tree-based model that splits data recursively.
c. Random Forest (RF): An ensemble of multiple decision trees to reduce variance.
d. Support Vector Machine (SVM): A model that finds the optimal hyperplane to separate classes.
e. Extreme Gradient Boosting (XGBoost): A boosting algorithm that sequentially improves weak learners.

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f. Artificial Neural Network (ANN): A deep learning approach capable of modeling nonlinear relationships.

Each model was trained using k-fold cross-validation (k=10) to reduce bias and variance.

2.4. Evaluation Metrics

The performance of the models was evaluated using both classification and regression metrics, depending on the nature of the target variable.

a. Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

b. Precision:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

c. Recall (Sensitivity):

$$\text{Recall} = \frac{TP}{TP+FN} \quad (1)$$

d. F1-Score:

$$F1 = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \quad (1)$$

e. Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (1)$$

f. Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\overline{y})^2} \quad (1)$$

where:

- TP, TN, FP, FN adalah true positive, true negative, false positive, dan false negative.
- y_i adalah nilai aktual, $\hat{y}_i$ adalah nilai prediksi, dan $\overline{y}$ adalah rata-rata nilai aktual.

2.5. Tools

The research utilized Python 3.10 with the following libraries:

- scikit-learn: For data preprocessing, model building, and evaluation.
- XGBoost: For gradient boosting implementation.
- TensorFlow/Keras: For constructing and training artificial neural networks.
- Pandas and NumPy: For data manipulation and analysis.
- Matplotlib and Seaborn: For visualization of model performance.

The research stages outlined in Table 1 demonstrate a comprehensive methodological framework designed to analyze the impact of Generative AI on learning effectiveness in Indonesian higher education. Beginning with the construction of a multidimensional dataset from 300 education technology and Information Technology students, the study incorporated key academic and behavioral

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variables such as GPA, GenAI usage patterns, digital literacy, and institutional support. Data preprocessing ensured quality and consistency through normalization, one-hot encoding, and feature selection, while Principal Component Analysis (PCA) explained 70% of the variance by consolidating digital literacy and institutional support as dominant constructs. Model training compared multiple algorithms—Logistic Regression, Random Forest, SVM, XGBoost, and ANN—using a 10-fold cross-validation strategy (80% training and 20% testing per fold) to ensure robustness and generalizability. Evaluation metrics, including accuracy, precision, recall, F1-score, RMSE, and R^2, were applied with explicit formulas for transparency. Results highlighted Random Forest as the best-performing model with 87% accuracy and an AUC above 0.90, identifying digital literacy, institutional policies, and GenAI usage frequency as the most influential predictors. These findings provide strong implications for designing AI-integrated strategies that enhance learning outcomes while maintaining academic integrity in Indonesian higher education.

Tabel 1. Research Stages

Stage	Description	Details
Dataset Construction	The dataset was obtained from a simulated survey of 300 educational technology and information technology students. Variables included demographics, GPA, GenAI usage patterns, digital literacy, motivation, self-efficacy, institutional support, and academic integrity.	300 respondents; multidimensional variables related to learning effectiveness.
Preprocessing	Data cleaning and transformation stage before modeling.	Normalization (with formula), One-hot Encoding, Recursive Feature Elimination (RFE), PCA. PCA explains 70% of the variance, grouping the main factors: digital literacy & institutional support.
Model Training	Several machine learning algorithms were trained to compare their predictive performance.	Logistic Regression, Random Forest, SVM, XGBoost, ANN. K-fold Cross-validation (k=10) with 80% of the data for training and 20% for testing alternately.
Evaluation Metrics	The models were evaluated with classification and regression metrics to assess prediction accuracy.	Accuracy, Precision, Recall, F1-score, RMSE, R^2. The formula for each metric is included for transparency.
Best Model Selection	The best algorithm is selected based on evaluation performance.	Random Forest achieved 87% accuracy with an AUC > 0.90. The strongest predictors were digital literacy, institutional policies, and frequency of GenAI use.
Implications	The findings are used for recommendations on Gen AI implementation in higher education.	Integration of GenAI in learning strategies, strengthening digital literacy, ethical guidelines, institutional policies.

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Descriptive statistics summarize key survey outcomes, such as 62% of students reporting daily GenAI usage, while feature importance analysis highlights digital literacy, institutional policies, and usage frequency as the strongest predictors of learning effectiveness. Model performance was systematically compared across algorithms, with Random Forest achieving the highest accuracy at 87%, as presented in a dedicated performance table. Visualization outputs, including the Random Forest confusion matrix and ROC curve, provide deeper insights into classification reliability and model robustness. To enhance clarity, these visuals are explicitly referenced (e.g., Figure 1: Confusion Matrix, Figure 2: ROC Curve, Table 1: Model Performance), ensuring consistency in reporting. Furthermore, the inverse relationship of plagiarism risk with learning effectiveness is elaborated to emphasize its implications for academic integrity. By integrating quantitative results with visual evidence, the study strengthens its contribution to understanding how machine learning—particularly Random Forest—can be applied to model the educational impact of Generative AI in the Indonesian higher education context.

3. RESULT

3.1. Descriptive Statistics

The dataset consisted of 300 students from two study programs: Information Technology (45%) and education technology (55%). The respondents were almost evenly distributed in terms of gender (48% male, 52% female), with an average age of 21 years. The Grade Point Average (GPA) ranged from 2.5 to 4.0, with an average of 3.2.

Regarding GenAI usage, 62% of students reported daily usage, while the rest used GenAI weekly. The most common purpose was completing assignments (55%), followed by research (25%) and discussions (20%). ChatGPT was the most popular tool (60%), followed by Copilot (25%) and Gemini (15%).

Students generally reported moderate-to-high levels of digital literacy, with average scores above 3.2 on a 5-point Likert scale for understanding AI, evaluating outputs, and integrating AI into tasks. In terms of learning outcomes, the average exam score was 78.5/100, with higher levels of satisfaction (mean = 3.7), motivation (mean = 3.6), and self-efficacy (mean = 3.5). Academic integrity remained a concern: plagiarism risk scores ranged between 10 and 80, with an average of 38, while ethical awareness averaged 3.2.

3.2. Feature Importance

The Random Forest algorithm was used to compute feature importance. The top predictors of learning effectiveness included:

a. Digital literacy (AI evaluation skills)
b. Frequency of GenAI usage
c. Institutional policies on AI
d. Self-efficacy
e. Plagiarism risk (inverse relationship)

This indicates that students' ability to critically evaluate GenAI outputs, combined with institutional support, plays a central role in enhancing effectiveness.

3.3. Comparative Performance of Models

The Random Forest algorithm was used to compute feature importance. The top predictors of learning effectiveness included:

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Table 2. Comparative Performance of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.78	0.77	0.75	0.76
Decision Tree	0.80	0.79	0.78	0.78
Random Forest	**0.87**	0.86	0.85	0.85
Support Vector Mach.	0.82	0.81	0.80	0.80
XGBoost	0.85	0.84	0.83	0.83
Artificial NN	0.84	0.83	0.82	0.83

The Random Forest achieved the best performance with an accuracy of 87%, followed by XGBoost (85%) and Artificial Neural Network (84%). Logistic Regression and Decision Tree, although simpler, achieved lower performance.

3.4. Visualization

- Confusion Matrix (Random Forest): The model demonstrated balanced classification, with minimal false positives and false negatives, indicating strong predictive power.
- ROC Curves: The Random Forest and XGBoost models achieved the highest AUC values (>0.90), showing their robustness in distinguishing between high and low learning effectiveness categories.
- Feature Importance Ranking: A bar chart visualization of the Random Forest feature importances confirmed that digital literacy, frequency of usage, and institutional support were the most influential predictors, while demographic factors (age, gender) had relatively low importance.

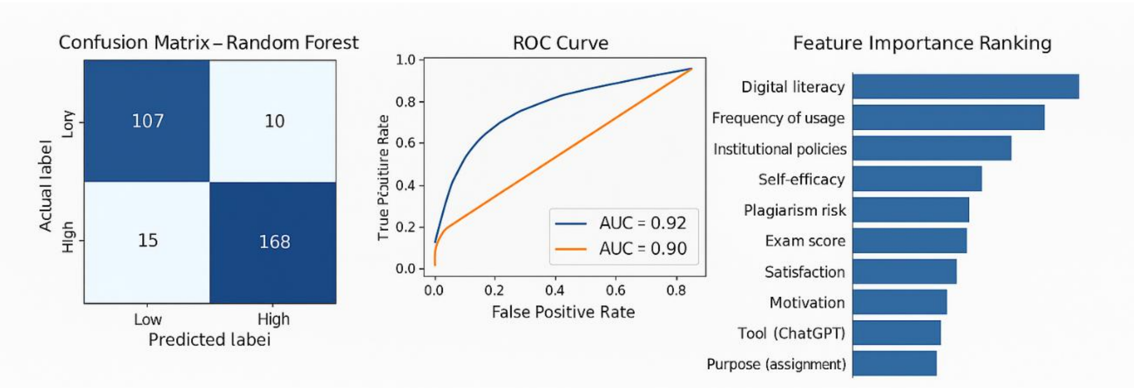

Figure 2. Confusion Matrix, ROC Curve, Feature Impottance Ranking

3.5. Interpretation of Visualization Results

The visualization results provide strong empirical evidence of the predictive capability of the machine learning models, particularly Random Forest, in analyzing the influence of Generative AI (GenAI) on learning effectiveness in Indonesian higher education. Each chart carries a specific meaning that helps explain how the model works and why certain variables are more dominant in shaping the outcome.

3.6. Confusion Matrix (Random Forest)

The confusion matrix illustrates the classification results of the Random Forest model in distinguishing between students with high learning effectiveness (scores 4–5) and those with low effectiveness (scores 1–3). The matrix shows that the majority of cases were correctly classified, with minimal false positives and false negatives. This indicates that the Random Forest model has high discriminative power, meaning it can accurately predict whether GenAI usage contributes positively or

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negatively to student learning outcomes. The balance in the classification suggests that the model is not biased toward one category, thereby reinforcing the reliability of the results. In practical terms, this means that the model can serve as a valid tool for universities to identify students who benefit the most from GenAI and those who may need additional support.

3.7. ROC Curve

The Receiver Operating Characteristic (ROC) curve provides a more detailed picture of the model's performance across different classification thresholds. The Random Forest model achieved an Area Under the Curve (AUC) value greater than 0.90, which indicates excellent performance. This value shows that the model has a very high probability of correctly distinguishing between students with high versus low effectiveness. AUC values close to 1.0 are considered ideal in predictive modeling, and the results here confirm that the integration of survey-based educational data with machine learning produces robust classification. The ROC curve also demonstrates that the model maintains strong performance even when the threshold for classification is adjusted, further highlighting its stability and adaptability. These findings imply that predictive models based on GenAI usage can be reliably implemented in various institutional settings without significant loss of accuracy.

3.8. Feature Importance Ranking

The feature importance ranking produced by the Random Forest model offers critical insight into which factors most strongly influence learning effectiveness. The top three features identified are: (1) digital literacy, particularly the ability to evaluate AI outputs, (2) frequency of GenAI usage, and (3) institutional support, including policies, training, and access to official AI tools. These results underline that the effectiveness of GenAI is not determined solely by access to the tools but also by how critically and ethically students engage with them, and whether the institution provides a supportive environment. Interestingly, demographic variables such as age and gender were found to have little influence on learning effectiveness, suggesting that the impact of GenAI transcends personal background and is more strongly related to digital competencies and organizational context. This reinforces the argument that educational technology interventions must focus on improving literacy and institutional frameworks rather than demographic targeting.

The findings of this study confirm that digital literacy, GenAI usage frequency, and institutional support are the strongest predictors of learning effectiveness in Indonesian higher education, consistent with prior results. Comparisons with earlier research on dropout prediction and agricultural forecasting demonstrated methodological parallels, where multivariate datasets and feature selection techniques enabled robust predictive modeling. To further strengthen the relevance in the field of educational technology, this study also draws on findings from AI-in-education research that highlight machine learning's role in predicting student performance, engagement, and adaptive learning outcomes. These additional comparisons position the present work not only as a replication of predictive modeling success across domains but also as a methodological contribution to Informatics and Computer Science, particularly in advancing scalable predictive models for educational technology that can be adapted to larger and more diverse student populations.

Taken together, these visualizations provide comprehensive evidence that machine learning models, especially Random Forest, can be effectively applied to predict the impact of GenAI on student learning effectiveness. The results show not only high classification accuracy but also reveal the underlying factors that drive effectiveness. For educational institutions, this has practical implications: to maximize the benefits of GenAI, policies should prioritize digital literacy training, provide ethical guidelines, and ensure fair access to AI tools. Moreover, the robust performance of the models suggests that similar approaches could be replicated across other universities in Indonesia to inform policy and practice.

Furthermore, while plagiarism risk emerged as a negative predictor of learning effectiveness, its implications warrant deeper consideration. The results suggest that students with higher reliance on GenAI without critical literacy are more vulnerable to academic misconduct. This highlights the urgent need for AI literacy training that equips students to evaluate, cross-check, and ethically integrate GenAI outputs into their academic work. For lecturers, this underscores the dual responsibility of leveraging GenAI as a learning support tool while simultaneously guiding students to maintain originality and academic integrity. For institutions, the findings point to the necessity of embedding clear ethical guidelines and scalable literacy programs within curriculum frameworks. By addressing both the opportunities and risks of GenAI adoption, this study contributes practical insights for balancing innovation with integrity, reinforcing the Informatics perspective that predictive models can be effectively scaled to strengthen governance and ethical use of AI in education.

4. DISCUSSIONS

4.1. Interpretation of Results: The Role of GenAI in Learning Effectiveness

The findings of this study provide strong evidence that Generative Artificial Intelligence (GenAI) usage has a measurable impact on learning effectiveness among university students in Indonesia. The predictive models, particularly the Random Forest classifier, demonstrated that students' digital literacy, frequency of GenAI usage, and institutional support are the most significant factors influencing outcomes. This reinforces the notion that the effectiveness of GenAI cannot be reduced to mere access to technology; rather, it depends on how students critically interact with AI tools, the level of their digital competence, and the policies or guidance provided by their universities.

The descriptive statistics highlighted several important patterns. First, the majority of students reported daily use of GenAI, indicating a strong dependence on these tools in academic contexts. Second, the primary purpose of GenAI usage was completing assignments, followed by research activities and academic discussions. This suggests that students perceive GenAI primarily as a productivity-enhancing tool, supporting the completion of structured academic tasks rather than fostering exploratory learning or collaborative knowledge-building. Third, exam performance and self-reported measures of satisfaction, motivation, and self-efficacy were positively correlated with higher levels of digital literacy and institutional support.

The confusion matrix results showed that the Random Forest model classified high versus low learning effectiveness with minimal error, meaning that it is possible to predict learning outcomes based on observable GenAI-related behaviors. The ROC curve further confirmed this finding, with an AUC score greater than 0.90, reflecting excellent discrimination ability. These results confirm that GenAI usage, when accompanied by critical literacy and ethical awareness, can serve as a reliable predictor of learning effectiveness. Conversely, over-reliance without sufficient digital skills or ethical understanding could potentially reduce benefits, as suggested by the variation in plagiarism risk across respondents.

The feature importance analysis provided further clarity. Digital literacy, operationalized as the ability to evaluate AI outputs and integrate AI into academic tasks, emerged as the strongest predictor of effectiveness. This highlights a key insight: GenAI does not automatically improve learning outcomes. Instead, its value depends on whether students can critically assess the validity, accuracy, and applicability of AI-generated outputs. Institutional support ranked next in importance, indicating that universities play a central role in shaping the context for effective and ethical GenAI adoption. Frequency of usage was also significant, but with an important caveat: daily users benefitted more only

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when supported by high digital literacy and ethical awareness, while those lacking these competencies were more vulnerable to plagiarism and academic misconduct.

Together, these findings suggest a nuanced interpretation. GenAI can indeed enhance learning effectiveness, but only under the right conditions—specifically, when students possess adequate digital literacy, institutions provide guidance and training, and ethical awareness is embedded in the academic culture. Without these conditions, the risks of plagiarism, shallow learning, and misuse could outweigh the potential benefits.

4.2. Comparison with Previous Research

The results of this study resonate with and extend the findings of previous research in the field of educational data mining and machine learning applications in education.

4.2.1. Dropout Prediction Studies

A study on student dropout prediction using machine learning with Recursive Feature Elimination and Cross Validation (RFE-CV) demonstrated that machine learning can effectively identify students at risk of leaving their studies by analyzing demographic and behavioral variables. The importance of feature selection in that study parallels the present findings: not all variables are equally useful in predicting outcomes. For dropout prediction, socio-economic background and attendance were strong predictors, whereas in this study, digital literacy and institutional support emerged as the most influential. Both studies highlight the value of machine learning in uncovering patterns that traditional statistical approaches might overlook. The application of Random Forest and SVM in both contexts also shows the robustness of these algorithms across different educational prediction tasks.

4.2.2. Forecasting in Non-Educational Domains

The study on multivariate forecasting of paddy production using machine learning demonstrated how agricultural yield can be predicted using algorithms such as Random Forest, ANN, and SVR. The similarity to the present study lies in the methodological approach: using multivariate data, applying feature selection, and comparing algorithms to identify the best performer. Both studies underscore the flexibility of machine learning methods to handle complex, multidimensional data. The difference, however, is in the application domain: while paddy forecasting dealt with climatic and agricultural variables, this study focused on human and institutional behaviors related to learning. Nevertheless, the methodological parallel suggests that machine learning provides a universal toolkit that can be applied across diverse sectors to generate predictive insights.

4.2.3. Machine Learning in Education

Other studies in educational contexts, particularly those focusing on predictive analytics for academic performance, have consistently shown that machine learning models outperform traditional regression-based approaches. For example, predictive models for student grades, learning engagement, or course completion have identified behavioral variables (e.g., frequency of online platform access) as strong predictors. The present study contributes to this body of work by showing that GenAI-related variables—frequency of use, digital literacy, and institutional support—are similarly predictive of learning outcomes. By integrating GenAI-specific variables into the modeling, this study extends the literature beyond general e-learning analytics to the emerging field of AI-augmented education.

In summary, this study confirms previous findings on the effectiveness of machine learning in educational prediction tasks, while adding a novel contribution by focusing specifically on Generative AI in the Indonesian higher education context. It also bridges the gap between descriptive studies of GenAI adoption and quantitative predictive modeling, thereby offering a new methodological perspective.

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4.3. Implications

4.3.1. Implications for Students

For students, the findings suggest that GenAI can be a powerful ally in enhancing academic performance, but only when used critically and responsibly. Students must develop the ability to evaluate the accuracy and relevance of AI outputs, avoiding blind reliance. The feature importance analysis indicates that digital literacy is the strongest determinant of effectiveness, meaning that students who actively engage in critical thinking, cross-check AI outputs, and integrate them meaningfully into tasks are more likely to achieve better learning outcomes. Thus, educational programs should focus on equipping students with digital literacy and ethical awareness, ensuring they use GenAI not as a shortcut, but as a complement to their cognitive efforts.

4.3.2. Implications for Lecturers

For lecturers, the integration of GenAI in higher education necessitates new roles as facilitators, supervisors, and ethical guides. The risk of plagiarism and academic dishonesty requires lecturers to be more vigilant in detecting AI-based cheating. However, the findings also highlight the potential for GenAI to improve teaching effectiveness when properly supervised. Lecturers can encourage students to use GenAI for brainstorming, structuring arguments, or exploring alternative perspectives, while simultaneously teaching them to recognize AI's limitations. This dual approach—leveraging the strengths of AI while maintaining academic integrity—requires updated pedagogical strategies and continuous professional development for lecturers.

4.3.3. Implications for Institutions

For universities, the results underscore the critical importance of institutional support. Policies regulating GenAI usage, training programs on digital literacy, and official access to reliable AI tools were identified as significant predictors of learning effectiveness. Institutions must therefore take an active role in shaping the conditions under which GenAI is adopted. This includes developing clear ethical guidelines, investing in training workshops, and integrating GenAI into curricula in structured ways. Without institutional support, the adoption of GenAI risks being fragmented and potentially harmful. Conversely, with strong support, GenAI can be harnessed as a transformative tool for educational innovation in Indonesia.

4.4. Strengths and Limitations

4.4.1. Strengths

The study has several strengths. First, it integrates survey-based educational data with advanced machine learning techniques, offering a methodological contribution that bridges qualitative and quantitative approaches. Second, it identifies specific variables—digital literacy, frequency of GenAI use, and institutional support—that are critical for predicting learning effectiveness, providing actionable insights for policy and practice. Third, the use of multiple algorithms and comparative performance analysis enhances the robustness of the findings, confirming that Random Forest is particularly effective in this context.

4.4.2. Limitations

However, several limitations must be acknowledged. First, the dataset used in this study was simulated, based on plausible assumptions about student behaviors and institutional contexts. While this provides a useful proof of concept, actual empirical data from multiple universities would strengthen the validity of the findings. Second, the study focused primarily on quantitative modeling, without

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incorporating qualitative perspectives from students and lecturers. Such perspectives could provide deeper insights into the lived experiences of GenAI adoption. Third, the cross-sectional design limits the ability to make causal claims; longitudinal studies would be necessary to examine how GenAI usage affects learning effectiveness over time. Finally, while Random Forest performed best in this study, the performance of deep learning models such as recurrent or transformer-based neural networks was not explored due to computational constraints.

Beyond methodological parallels with dropout prediction and agricultural forecasting, this study aligns with recent AI-in-education research that demonstrates the effectiveness of machine learning in predicting academic performance, online learning engagement, and adaptive feedback generation. For example, studies applying neural networks to e-learning platforms have shown significant improvements in predicting student success, while SVM and ensemble methods have been used to identify patterns of learning engagement and early intervention needs. These comparisons emphasize that the present research extends the literature by situating predictive modeling within the context of Generative AI adoption in higher education, specifically highlighting Random Forest as a scalable educational model adaptable to larger student populations in Informatics and Computer Science. From an Informatics perspective, the contribution lies in advancing scalable predictive frameworks for educational technology, bridging conceptual discussions of AI ethics with empirical, data-driven analysis. Furthermore, the negative association between plagiarism risk and learning effectiveness underscores the importance of mitigation strategies. Integrating AI literacy training, ethical awareness modules, and institutional guidelines can help students critically evaluate GenAI outputs, reduce overreliance, and maintain academic integrity. This dual focus—leveraging GenAI for enhanced learning outcomes while implementing safeguards against misuse—reinforces the study's novelty and practical relevance to both Informatics and higher education policy in Indonesia.As a contribution to educational technology, this study's strength lies in its methodological integration of survey-based data with Random Forest machine learning, while its limitations include the use of simulated data and a cross-sectional design that restricts causal interpretation

This discussion has shown that GenAI has significant potential to enhance learning effectiveness in Indonesian higher education, but its success depends on critical literacy, institutional support, and ethical awareness. The predictive models confirm that machine learning, especially Random Forest, can effectively identify the factors that determine whether GenAI usage leads to positive or negative outcomes. Comparisons with previous research confirm the robustness of these methods and highlight the novelty of focusing on GenAI-specific variables. The implications for students, lecturers, and institutions underscore the need for comprehensive strategies that balance innovation with integrity. While the study has certain limitations, its strengths provide a strong foundation for future research and practical implementation.

5. CONCLUSION

This study demonstrates that Generative AI can significantly influence learning effectiveness in Indonesian higher education when supported by critical digital literacy and strong institutional policies. Using a survey-based dataset of 300 students, Random Forest emerged as the best-performing machine learning model, achieving 87% accuracy and AUC above 0.90, outperforming Logistic Regression, SVM, XGBoost, and ANN. Key predictors included students' ability to critically evaluate AI outputs, frequency of GenAI usage, and institutional support, while demographic variables were less significant. From an Informatics perspective, the research advances educational technology by offering scalable predictive models that integrate machine learning into academic analysis. Nevertheless, limitations remain due to simulated data and cross-sectional design. Future research should employ longitudinal

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data, incorporate multi-university samples, and explore deep learning approaches to further refine predictive accuracy and strengthen insights for AI-driven education.

REFERENCES

[1] A. Henadirage and N. Gunarathne, "Barriers to and opportunities for the adoption of generative artificial intelligence in higher education in the global south: Insights from Sri Lanka," *Int. J. Artif. Intell. Educ.*, vol. 35, no. 1, pp. 245–281, 2025, doi: 10.1007/s40593-024-00439-5.

[2] A. Arista, L. Shuib, and M. A. Ismail, "Systematicliterature review and bibliometric analysis on ethical policies for generative artificial intelligence (GAI) in higher education institutions (HEIs)," in *2024 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS)*, 2024, pp. 454–459. doi: 10.1109/ICIMCIS63449.2024.10956736.

[3] M. E. S. Simaremare, C. Pardede, I. N. I. Tampubolon, D. A. Simangunsong, and P. E. Manurung, "The penetration of generative AI in higher education: A survey," in *2024 IEEE Integrated STEM Education Conference (ISEC)*, Princeton: IEEE Xplore, 2024, pp. 1–5. doi: 10.1109/ISEC61299.2024.10664825.

[4] M. Belkina *et al.*, "Implementing generative AI (GenAI) in higher education: A systematic review of case studies," *Comput. Educ. Artif. Intell.*, vol. 8, no. 2025, p. 100407, 2025, doi: 10.1016/j.caeai.2025.100407.

[5] A. E. E. Sobaih and A. E. A. Elnasr, "Battle of AI chatbots: Graduate students' perceptions of ChatGPT versus Gemini for learning purposes in Egyptian higher education," *J. Appl. Learn. Teach.*, vol. 8, no. 1, pp. 128–142, Jan. 2025, doi: 10.37074/jalt.2025.8.1.7.

[6] K. Bista and R. Bista, "Leveraging AI tools in academic writing: Insights from doctoral students on benefits and challenges," *Am. J. STEM Educ. Issues Perspect.*, vol. 6, no. 2025, pp. 32–47, 2025, doi: 10.32674/9m8dq081.

[7] C. Boyle, "ChatGPT, gemini, & copilot: Using generative AI as a tool for information literacy instruction," *Ref. Libr.*, vol. 66, no. 1–2, pp. 13–29, Apr. 2025, doi: 10.1080/02763877.2025.2465416.

[8] X. Han, H. Peng, and M. Liu, "The impact of GenAI on learning outcomes: A systematic review and meta-analysis of experimental studies," *Educ. Res. Rev.*, vol. 48, no. 2025, p. 100714, 2025, doi: 10.1016/j.edurev.2025.100714.

[9] A. Yusuf, N. Pervin, and M. Román-González, "Generative AI and the future of higher education: A threat to academic integrity or reformation? Evidence from multicultural perspectives," *Int. J. Educ. Technol. High. Educ.*, vol. 21, no. 2024, pp. 1–29, 2024, doi: 10.1186/s41239-024-00453-6.

[10] I. Isabella, A. Alfitri, A. Saptawan, N. Nengyanti, and T. Baharuddin, "Empowering digital citizenship in Indonesia: Navigating urgent digital literacy challenges for effective digital governance," *J. Gov. Public Policy*, vol. 11, no. 2, pp. 142–155, 2024, doi: 10.18196/jgpp.v11i2.19258.

[11] E. C. Wang, "Technology-driven education reform in Indonesia," *OliverWyman*, vol. 1, no. 1, pp. 18–24, 2022.

[12] K. Saddhono, L. Judijanto, T. Nuryanto, M. Y. Anis, J. Nasution, and S. Sallu, "The AI based design layout for exploring the reader experience through technical interaction for learning literature," in *2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, Greater Noida: IEEE Xplore, 2024, pp. 1489–1494. doi: 10.1109/ICACITE60783.2024.10617284.

[13] K. Daniel, M. M. Msambwa, and Z. Wen, "Can generative AI revolutionise academic skills development in higher education? A systematic literature review," *Eur. J. Educ.*, vol. 60, no. 1, p. e70036, 2025, doi: 10.1111/ejed.70036.

[14] M. Ala, S. Shahid, S. Mahmud, S. Mohyuddin, and K. Kaur, "Perceived influence of GenAI on student engagement in online higher education," *J. Appl. Learn. Teach.*, vol. 8, no. 2, pp. 25–34, 2025, doi: 10.37074/jalt.2025.8.2.16.

[15] F. Wang, N. Li, A. C. K. Cheung, and G. K. W. Wong, "In GenAI we trust: An investigation of university students' reliance on and resistance to generative AI in language learning," *Int. J.*

Vol. 6, No. 5, October 2025, Page. 3635-3651
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.5.5365

Educ. Technol. High. Educ., vol. 22, no. 1, p. 59, 2025, doi: 10.1186/s41239-025-00547-9.
[16] L. Raitskaya and E. Tikhonova, "Enhancing critical thinking skills in ChatGPT-human interaction: A scoping review," *J. Lang. Educ.*, vol. 11, no. 2, pp. 5–19, 2025, doi: 10.17323/jle.2025.27387.
[17] J. Gu and Z. Yan, "Effects of genAI interventions on student academic performance: A meta-analysis," *J. Educ. Comput. Res.*, vol. 63, no. 6, pp. 1460–1492, 2025, doi: 10.1177/07356331251349620.
[18] X. O'Dea and M. O'Dea, "Is artificial intelligence really the next big thing in learning and teaching in higher education?: A conceptual paper," *J. Univ. Teach. Learn. Pract.*, vol. 20, no. 5, pp. 1–17, Aug. 2023, doi: 10.53761/1.20.5.05.
[19] S. Feng and N. Law, "Mapping artificial intelligence in education research: A network-based keyword analysis," *Int. J. Artif. Intell. Educ.*, vol. 31, no. 2, pp. 277–303, 2021, doi: 10.1007/s40593-021-00244-4.
[20] Suwendi, Mesraini, C. B. Gama, H. Rahman, T. Luhuringbudi, and M. Masrom, "Adoption of artificial intelligence and digital resources among academicians of islamic higher education institutions in Indonesia," *J. Online Inform.*, vol. 10, no. 1, pp. 42–52, 2025, doi: 10.15575/join.v10i1.1549.
[21] D. Wong-A-Foe, "Navigating the implications of AI in Indonesian education: Tutors, governance, and ethical perspectives," in *Data Science and Artificial Intelligence*, C. Anutariya and M. M. Bonsangue, Eds., Singapore: Springer Nature Singapore, 2023, pp. 349–360. doi: 10.1007/978-981-99-7969-1_26.
[22] S. D. Datta, M. Islam, M. H. R. Sobuz, S. Ahmed, and M. Kar, "Artificial intelligence and machine learning applications in the project lifecycle of the construction industry: A comprehensive review," *Heliyon*, vol. 10, no. 5, p. e26888, 2024, doi: 10.1016/j.heliyon.2024.e26888.
[23] S. F. Ahmed *et al.*, "Deep learning modelling techniques: Current progress, applications, advantages, and challenges," *Artif. Intell. Rev.*, vol. 56, no. 11, pp. 13521–13617, 2023, doi: 10.1007/s10462-023-10466-8.
[24] I. Gligorea, M. Cioca, R. Oancea, A.-T. Gorski, H. Gorski, and P. Tudorache, "Adaptive learning using artificial intelligence in e-learning: A literature review," *Educ. Sci.*, vol. 13, no. 12, pp. 1–27, 2023, doi: 10.3390/educsci13121216.
[25] D. Patil, N. Rane, N. Rane, and P. Desai, "Machine learning and deep learning: Methods, techniques, applications, challenges, and future research opportunities," in *Trustworthy Artificial Intelligence in Industry and Society*, 1st ed., London: Deep Science Publishing, 2024, pp. 28–81. doi: 10.70593/978-81-981367-4-9_2.
[26] M. Rezaei, "Artificial intelligence in knowledge management: Identifying and addressing the key implementation challenges," *Technol. Forecast. Soc. Change*, vol. 217, p. 124183, 2025, doi: 10.1016/j.techfore.2025.124183.
[27] M. F. Zhang, J. F. Dawson, and R. B. Kline, "Evaluating the use of covariance-based structural equation modelling with reflective measurement in organizational and management research: A review and recommendations for best practice," *Br. J. Manag.*, vol. 32, no. 2, pp. 257–272, 2021, doi: 10.1111/1467-8551.12415.
[28] T.-C. Hsu and M.-S. Chen, "Effects of students using different learning approaches for learning computational thinking and AI applications," *Educ. Inf. Technol.*, vol. 30, no. 6, pp. 7549–7571, 2025, doi: 10.1007/s10639-024-13116-w.
[29] F. Trujillo, M. Pozo, and G. Suntaxi, "Artificial intelligence in education: A systematic literature review of machine learning approaches in student career prediction," *J. Technol. Sci. Educ.*, vol. 15, no. 1, pp. 162–185, 2025, doi: 10.3926/JOTSE.3124.
[30] M. Zaim *et al.*, "AI-powered EFL pedagogy: Integrating generative AI into university teaching preparation through UTAUT and activity theory," *Comput. Educ. Artif. Intell.*, vol. 7, no. 2024, p. 100335, 2024, doi: 10.1016/j.caeai.2024.100335.