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Comparative Analysis of Machine Learning Models for Pedagogical Decision Support: Balancing Accuracy and Interpretability in Learning Analytics

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ABSTRACT

This article presents a comprehensive overview of a comparative analysis of three machine learning models Decision Tree, Random Forest, and XGBoost as tools for pedagogical decision support. As education becomes increasingly digitized, the focus of analytics is shifting from retrospective problem diagnosis to the proactive generation of actionable insights that help educators optimize the learning process. This study evaluates the models not only on their predictive accuracy but also on the interpretability of their results, a key factor for practical application in learning analytics. The methodology involved training and testing the models on a synthetic dataset simulating student behavior. The results demonstrated high predictive efficacy across all models, with accuracy ranging from 98% to 100%. The Decision Tree achieved 99% accuracy with complete logical transparency, making it a valuable tool for generating global pedagogical heuristics. XGBoost reached 100% accuracy, but its "black-box" nature necessitates the use of Explainable AI (XAI) methods for generating personalized insights. A key finding across all models was the high predictive power of behavioral indicators, such as the number of missed classes and assignment completion rates, confirming their importance in identifying students in need of support. This highlights the potential for such models to move beyond simple prediction and provide educators with targeted, evidence-based insights for timely intervention. The principal conclusion is the need for hybrid systems that synergistically combine the accuracy of complex models with the interpretability required for effective decision support in education.

Keywords: Artificial intelligence, Learning analytics, Explainable AI, Education system, Data analysis, Decision support

INTRODUCTION

The modern educational landscape is undergoing a fundamental transformation driven by the widespread adoption of digital technologies. Learning Management Systems (LMS), Massive Open Online Courses (MOOCs), and other educational platforms generate unprecedented volumes of data on student interactions with learning content, their behavior, and academic performance (Shaporeva et al., 2022). This phenomenon opens unique opportunities for the in-depth analysis and improvement of educational processes.

In response to this challenge, interdisciplinary fields such as Educational Data Mining (EDM) and Learning Analytics (LA) have emerged (Romero & Ventura, 2020). While EDM is more focused on the technical aspects and automatic pattern detection, LA emphasizes human sense-making and the use of data to improve teaching and learning (Chen et al., 2023; Haleem et al., 2022; Ngwu et al., 2025; Romero & Ventura, 2020). The primary goal of these fields is to shift from reactive to proactive educational strategies (Bhushan et al., 2023). Instead of merely identifying learning difficulties at the end of a semester, predictive analytics allows for the early identification of students who show indicators of needing intervention (Chen et al., 2023).

However, as the field evolves, the research focus is shifting from simple prediction to the more complex task of supporting pedagogical decision-making (López-Meneses et al., 2025; Gomez et al., 2025; Gunasekara & Saarela, 2025; Villegas-Ch et al., 2025). The relevant question today is not only whether a student will successfully complete a course, but how they can be helped to achieve better results. This concept involves not just predicting an outcome but generating actionable insights for educators (Haleem et al., 2022). Providing information that a student is at risk has limited value. It is far more important to explain which specific aspects – be it class attendance, low platform activity, or difficulties with certain topics – are the cause of the predicted risk (Mastour et al., 2025).

Thus, modern learning analytics faces the challenge of balancing the accuracy of predictive models with their interpretability. It is necessary to create models that not only predict but also provide educators and administrators with practical, explainable, and actionable recommendations (Ab Rahman et al., 2024). The scientific novelty of this work lies in shifting the focus from a purely technical competition of models based on accuracy metrics to a holistic assessment of their suitability as tools for supporting pedagogical decisions. This research directly addresses a gap in the literature related to the lack of systematic comparisons of models from different points on the "accuracy-interpretability" spectrum for solving diagnostic, rather than predictive, tasks in learning analytics.

LITERATURE REVIEW AND PROBLEM STATEMENT

The Rise of Data-Driven Decision-Making in Education

The potential of LA and EDM lies in their ability to transform vast amounts of educational data into practical knowledge, enabling a shift from reactive to proactive pedagogical strategies (López-Meneses et al., 2025; Bhushan et al., 2023). The goal is not to predict failure but to provide educators with tools for timely, data-driven support (Bhushan et al., 2023; Puthanveettil Madathil et al., 2025). This shifts the task of analytics from stating a fact to providing opportunities for improving the educational experience of every student.

The Accuracy-Interpretability Spectrum

The choice of a machine learning model is a key decision that determines not only the accuracy of predictions but also their practical applicability. In the EDM literature, a continuum of approaches can be identified: from simple and transparent "white-box" models to complex, highly accurate, but opaque "black-box" models. The choice of a model often represents a trade-off between these two goals (Tang et al., 2024). A strategic selection of models covering different points on this spectrum allows for a systematic investigation of the trade-off itself, which is a more profound task than a simple comparison of metrics (Bhushan et al., 2023).

Decision Trees (DT) are central among "white-box" models (Puthanveettil Madathil et al., 2025; Bulut et al., 2025). This algorithm builds a hierarchical structure of "IF-THEN" rules, which allows for a clear demonstration of the classification logic and fosters trust from non-technical specialists (Gomez et al., 2025). The strengths of DT are high interpretability and ease of visualization. However, they are prone to overfitting and can be unstable (Gunasekara & Saarela, 2025).

Ensemble methods, such as Random Forest (RF) and Gradient Boosting (XGBoost), are considered "black-box" models (Ngwu et al., 2025; Romero & Ventura, 2020). Random Forest creates many decision trees, which helps to reduce the tendency to overfit and increase accuracy (Granitto et al., 2006; Breiman, 2001). Gradient Boosting and its implementation XGBoost build trees sequentially, where each subsequent tree corrects the errors of the previous one, allowing for the highest accuracy (Lundberg & Lee, 2017; Chen & Guestrin, 2016). However, combining hundreds of trees makes tracking the decision-making logic nearly impossible.

Deep Learning models, such as Artificial Neural Networks (ANN), represent the pinnacle of predictive accuracy but are the quintessential "black box," making their understanding by humans almost impossible (Salem & Shaalan, 2025; Lee et al., 2023).

The Imperative of Explainability and the Rise of Explainable AI (XAI)

In the educational context, accuracy alone is insufficient. A decision made by a "black box" remains useless if the end-users – teachers, administrators, and students – cannot trust and act upon it (Villegas-Ch et al., 2025; Adnan et al., 2021). This lack of trust is one of the main reasons for the slow adoption of AI tools in education (Nnadi et al., 2024).

In response to this challenge, the field of Explainable AI (XAI) is actively developing (Nnadi et al., 2024; Villegas-Ch et al., 2025; Ab Rahman et al., 2024). XAI offers post-hoc explanation methods that allow for the interpretation of predictions from even the most complex models. The most popular among them are LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) (Mastour et al., 2025; Ab Rahman et al., 2024; Tang et al., 2024; Adnan et al., 2021; Lundberg & Lee, 2017; Chen & Guestrin, 2016). LIME provides local explanations for individual predictions, while SHAP, based on game theory, offers a more mathematically rigorous way to assess the contribution of features at both local and global levels (Ab Rahman et al., 2024; Adnan et al., 2021). The integration of XAI allows for a shift from a simple trade-off between accuracy and interpretability to a synergy, achieving high accuracy and then applying XAI methods to explain it (Misinem et al., 2024; Villegas-Ch et al., 2025; Lee et al., 2023).

METHODS

Purpose and Objectives of the Study

The purpose of this study is a comparative analysis of three machine learning models – Decision Tree, Random Forest, and Gradient Boosting – for analyzing factors that influence students' educational trajectories, with the goal of supporting pedagogical decision-making, as well as evaluating their effectiveness in terms of accuracy and interpretability.

To achieve this purpose, the following objectives were set:

Select machine learning models that represent different points on the accuracy-interpretability spectrum.

Describe the experimental methodology, including the dataset characteristics and evaluation criteria.

Conduct training and testing of the models and compare their results based on accuracy metrics and the quality of analytical conclusions.

Formulate recommendations for creating decision support systems based on the synergy of models with varying degrees of interpretability.

Materials and Methods

To address the stated objective, three machine learning models were selected:

Decision Tree Classifier as a baseline, fully interpretable ("white-box") model.

Random Forest Classifier as an ensemble model representing a balance between accuracy and complexity.

XGBoost (Extreme Gradient Boosting) as a state-of-the-art "black-box" model demonstrating the highest accuracy.

Mathematical Description of Models

Decision Tree. The model builds a classification by recursively partitioning the feature space based on a criterion that minimizes uncertainty, such as the *Gini* index:

$$Gini(D) = 1 - \sum_{k=1}^{k} p_k^2 \quad (1)$$

Where p_k is the proportion of objects of class k in subset D.

Random Forest. The model is an ensemble of N independent trees. The final decision is made by voting:

$$\hat{y} = mode\{h_1(x), h_2(x), \dots, h_N(x)\} \quad (2)$$

Where $h_i(x)$ is the result of the i-th tree.

XGBoost. The model sequentially builds an ensemble of trees, where each subsequent tree corrects the errors of the previous one. A regularized loss function is minimized:

$$\tau = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{t=1}^{T} \Omega(f_t) \quad (3)$$

Where $\Omega(f_t) = \gamma T + \frac{1}{2}\lambda\|\varpi\|^2$ is the regularization on the number of leaves and weights; $l(y_i, \hat{y}_i)$ is the loss function.

Dataset and Experimental Methodology

For the experiment, a synthetic dataset of 1000 records was generated to simulate student activity. The use of synthetic data allowed for the creation of a controlled environment for a pure comparison of model interpretability, presenting the study as a proof-of-concept. The dataset included features: percentage of completed assignments, average grade, time on the platform, chat activity, and number of missed classes. The target variable was an indicator of the need for support, assigned based on logical rules (e.g., if the number of missed classes > 5, the class "Absences" was assigned).

The data was split into training (70%) and testing (30%) sets. Accuracy, Precision, Recall, and F1-score were used for evaluation. The hyperparameters of the models (Table I) were chosen to ensure a balance between accuracy and protection against overfitting.

Table I. Hyperparameters of the Models

Model	Key Parameters	Interpretability	Robustness	Rationale for Selection
Decision Tree	max_depth=4, random_state=42	High	Medium	Simple structure, explainable logic
Random Forest	n_estimators=100, max_depth=6	Medium	High	Ensemble approach reduces variance
XGBoost	n_estimators=100, learning_rate=0.1	Low	Very High	Best accuracy and robustness

RESULTS

A comparative analysis of the models' performance on the test set is presented in Table 2.

Table 2. Comparative Performance Metrics of the Models

Model	Accuracy	Macro Avg F1-score	Key Observations
Decision Tree	99.0%	0.96	High accuracy with full interpretability. Minor errors only for the "Inactive" class.
Random Forest	98.0%	0.86	High overall accuracy, but a significantly lower F1-score for the rare "Inactive" class (0.40).
XGBoost	100%	1.00	Perfect accuracy across all metrics, error-free classification of all classes.

The results presented in Table II clearly show that all three models achieved high levels of accuracy, with XGBoost reaching a perfect score. The Decision Tree model also performed exceptionally well, with 99% accuracy, while offering the significant advantage of being fully interpretable. Notably, the Random Forest model, despite its high overall accuracy, struggled with the rare "Inactive" class, as indicated by its low F1-score. This suggests that while ensemble methods can be powerful, they may require careful tuning when dealing with imbalanced datasets, a common challenge in educational contextsThe feature importance analysis, conducted for all three models, showed similar results: the most dominant factor is the "number of missed classes," followed by "percentage of completed assignments" and "average grade." This confirms that the models correctly captured the logical rules embedded in the data.

A key result of the Decision Tree model was the visualization of the decision tree (Figure I), which clearly demonstrates the classification logic.

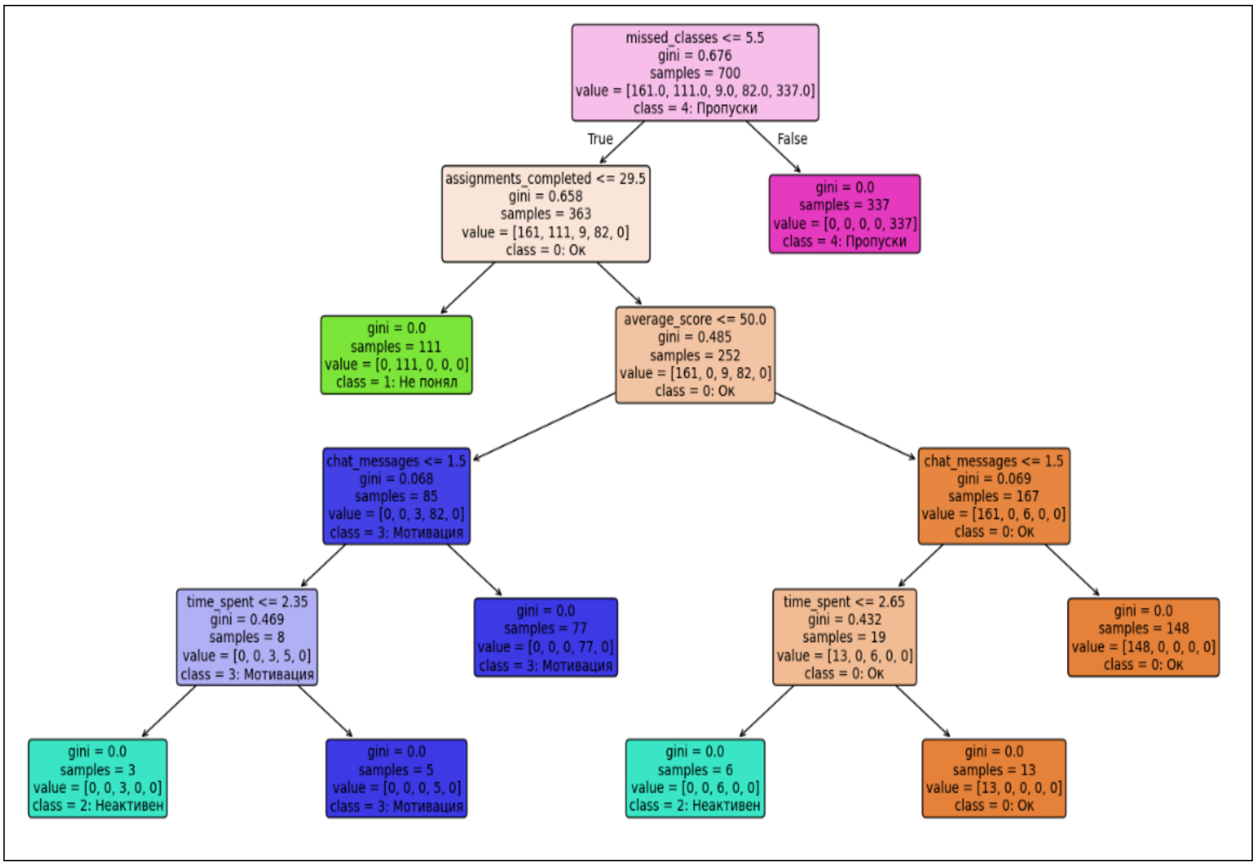

Figure I. Decision Tree for Analyzing Educational Trajectories

The primary splitting node is the check on the number of absences. This result is not just a prediction but a ready-to-use set of transparent pedagogical heuristics.

DISCUSSION

The Synthetic Data Problem and Reinterpretation of Results

The experimental results confirm the high efficiency of the models, but the ideal accuracy (99–100%) is a direct consequence of using synthetic data. In real-world conditions, educational data contains significantly more "noise," and achieving such accuracy is unlikely (Bhushan et al., 2023; Puthanveettil Madathil et al., 2025; Bulut et al., 2025; Villegas-Ch et al., 2025). The main limitation of this study is the use of synthetic data, which can suffer from distribution mismatch with real data, lack of realism and outliers, and inherited bias (Romero & Ventura, 2020; Granitto et al., 2006; Chen & Guestrin, 2016; Lundberg & Lee, 2017; Salem & Shaalan, 2025; Lee et al., 2023; Adnan et al., 2021).

Nevertheless, this limitation allows for a reinterpretation of the work's contribution. The high accuracy serves as a controlled starting point for a pure comparison of the models' interpretability. The study becomes an investigation of how models explain their decisions when the "what" (the prediction) remains nearly perfect.

From Trade-off to Synergy: A Hybrid Decision Support System

The comparison of the models reveals their strengths for different pedagogical tasks.

Decision Tree (99% accuracy), being a "white-box," provides full interpretability. Its logical rules can be directly translated into recommendations for teachers and used to develop general institutional policies.

XGBoost (100% accuracy), as a "black-box," ensures maximum accuracy in identifying students who require attention, especially in complex, non-linear cases. However, its conclusions require additional interpretation.

Random Forest (98% accuracy) occupies an intermediate position but showed weakness in handling imbalanced classes (F1-score of 0.40 for the "Inactive" class), which is a significant limitation for real-world data.

Instead of choosing a single model, we propose a hybrid or multi-level approach as the optimal solution for a pedagogical decision support system:

Level 1 (Global Heuristics): Use Decision Tree to generate simple, reliable, and globally applicable rules that form the basis of general teaching strategies.

Level 2 (High-Precision Identification): Use XGBoost for the accurate identification of students whose behavioral patterns are too complex for a simple tree.

Level 3 (Personalized Insights): Apply XAI methods (SHAP or LIME) to the XGBoost predictions to generate personalized explanations that inform the teacher why a student was flagged by the system.

This approach allows a shift from a "trade-off" to a "synergy," combining the accuracy of complex models with the interpretability needed for action (Nnadi et al., 2024; Lee et al., 2023). The research question moves from "Which model is better?" to "How can we design an effective system for decision support by synergistically combining models with different strengths?".

To help select the appropriate tool, a conceptual framework is presented in Table 3.

Table 3. Conceptual Framework for Model Selection in Decision Support Systems

Criterion	Decision Tree (White-Box)	Random Forest (Ensemble)	XGBoost + XAI (Explainable Black-Box)
Predictive Accuracy	High	Very High	State-of-the-Art
Type of Interpretability	Intrinsic / Global	Post-hoc / Global	Post-hoc / Local & Global
Nature of Insights	Simple pedagogical heuristics	Identification of key predictors	Personalized, diagnostic insights
Primary Use Case	Developing general early-warning criteria	Segmenting the student population	Generating personalized feedback
Trust and Applicability	High trust, direct action rules	Moderate trust, informs general strategy	High trust (with quality explanation)

Ultimately, the framework presented in Table III serves as a practical guide for educational stakeholders. It illustrates that the optimal choice of a machine learning model is not a matter of selecting the one with the highest accuracy, but rather aligning the model's characteristics with the specific pedagogical goal. For developing broad, institution-wide policies, the transparency of a Decision Tree is invaluable. In contrast, for providing targeted, individual support to a student exhibiting complex patterns of behavior, the precision of an XGBoost model, coupled with XAI for explanation, offers a more powerful solution. This nuanced approach ensures that technology serves pedagogy, rather than the other way around, leading to more effective and trusted data-driven interventions.

CONCLUSIONS

The conducted research has demonstrated that modern machine learning algorithms can be successfully applied to analyze factors influencing student learning, addressing an important task in learning analytics. The choice of a specific model should be determined by the balance between the requirements for accuracy and the need for interpretability of the results. XGBoost is the most accurate model, while Decision Tree remains a valuable tool due to its complete transparency.

Future research should focus on overcoming the limitations of the current work, primarily verification using real data. The main task is to test the proposed hybrid approach on real anonymized data from educational systems (LMS, MOOC). Second, integration with XAI methods, since highly accurate models such as XGBoost require the implementation of explainable artificial intelligence methods (e.g., SHAP, LIME) (Mastour et al., 2025; Ab Rahman et al., 2024; Adnan et al., 2021; Misinem et al., 2024; Nnadi et al., 2024; Lundberg & Lee, 2017; Chen & Guestrin, 2016; Lee et al., 2023). This will allow us to combine high accuracy with the provision of understandable and practical explanations for educators.The results of this study can form the basis for creating interactive decision support systems that provide teachers with real-time information about students needing support and, more importantly, the likely reasons for their difficulties. Ultimately, further development in this direction will contribute to the creation of more adaptive and personalized educational environments, where AI technologies serve not for control, but for the deep understanding and support of every learner.

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REFERENCES

Ab Rahman, N. F., Wang, S. L., Ng, T. F., & Ghoneim, A. S. (2024), Artificial Intelligence in Education: A Systematic Review of Machine Learning for Predicting Student Performance. Journal of Advanced Research in Applied Sciences and Engineering Technology, 54(1), 198–221. https://doi.org/10.37934/araset.54.1.198221

Adnan, M. et al. (2021), Predicting at-Risk Students at Different Percentages of Course Length for Early Intervention Using Machine Learning Models. IEEE Access, 9, 7519-7539. https://doi.org/10.1109/ACCESS.2021.3049446

Bhushan, M., Vyas, S., Mall, S. et al. (2023), A comparative study of machine learning and deep learning algorithms for predicting student's academic performance. Int J Syst Assur Eng Manag, 14, 2674–2683. https://doi.org/10.1007/s13198-023-02160-3

Breiman, L. (2001), Random Forests. Machine Learning, 45, 5–32. https://doi.org/10.1023/A:1010933404324

Bulut, O., Tan, B., Mazzullo, E., & Syed, A. (2025), Benchmarking Variants of Recursive Feature Elimination: Insights from Predictive Tasks in Education and Healthcare. Information, 16(6), 476. https://doi.org/10.3390/info16060476

Chen, T., & Guestrin, C. (2016), XGBoost: A scalable tree boosting system. In: Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining, 785-794. https://doi.org/10.1145/2939672.2939785

Chen, Z., Cen, G., Wei, Y. and Li, Z. (2023), Student Performance Prediction Approach Based on Educational Data Mining. IEEE Access, 11, 131260-131272. https://doi.org/10.1109/ACCESS.2023.3335985

Gomez, M. J., Armada Sánchez, Á., Albaladejo-González, M., Garcia Clemente, F. J., & Ruipérez-Valiente, J. A. (2025), Utilising Explainable AI to Enhance Real-Time Student Performance Prediction in Educational Serious Games. Expert Systems, 42, e70008. https://doi.org/10.1111/exsy.70008

Granitto, P. M., Furlanello, C., Biasioli, F., & Gasperi, F. (2006), Recursive feature elimination with random forest for PTR-MS analysis of agroindustrial products. Chemometrics and Intelligent Laboratory Systems, 83(2), 83-90. https://doi.org/10.1016/j.chemolab.2006.01.007

Gunasekara, S., & Saarela, M. (2025), Explainable AI in Education: Techniques and Qualitative Assessment. Applied Sciences, 15(3), 1239. https://doi.org/10.3390/app15031239

Haleem, A., Javaid, M., Qadri, M. A., & Suman, R. (2022), Understanding the Role of Digital Technologies in Education: A Review. Sustainable Operations and Computers, 3, 275-285. https://doi.org/10.1016/j.susoc.2022.05.004

Lee, J. E., Jindal, A., Patki, S. N., Gurung, A., Norum, R., & Ottmar, E. (2023), A comparison of machine learning algorithms for predicting student performance in an online mathematics game. Interactive Learning Environments, 32(9), 5302–5316. https://doi.org/10.1080/10494820.2023.2212726

López-Meneses, E., Mellado-Moreno, P. C., Gallardo Herrerías, C., & Pelícano-Piris, N. (2025), Educational Data Mining and Predictive Modeling in the Age of Artificial Intelligence: An In-Depth Analysis of Research Dynamics. Computers, 14(2), 68. https://doi.org/10.3390/computers14020068

Lundberg, S. M., & Lee, S. I. (2017), A unified approach to interpreting model predictions. In: Advances in neural information processing systems, 4765-4774.

Mastour H, Dehghani T, Moradi E, Eslami S. (2025), Explainable artificial intelligence for predicting medical students' performance in comprehensive assessments. Sci Rep, 15(1), 23752. https://doi.org/10.1038/s41598-025-07460-1

Misinem, M., Kurniawan, T., Dewi, D., Zakaria, M., & Nazmi, C. (2024), Leveraging Data Analytics for Student Grade Prediction: A Comparative Study of Data Features. Journal of Applied Data Sciences, 5(4), 2025-2038. https://doi.org/10.47738/jads.v5i4.442

Ngwu, C., Liu, Y. & Wu, R. (2025), Reinforcement learning in dynamic job shop scheduling: a comprehensive review of AI-driven approaches in modern manufacturing. J Intell Manuf. https://doi.org/10.1007/s10845-025-02585-6

Nnadi, L. C., Watanobe, Y., Rahman, M. M., & John-Otumu, A. M. (2024), Prediction of Students' Adaptability Using Explainable AI in Educational Machine Learning Models. Applied Sciences, 14(12), 5141. https://doi.org/10.3390/app14125141

Puthanveettil Madathil, A., Luo, X., Liu, Q., Walker, C., Madarkar, R., & Qin, Y. (2025), A review of explainable artificial intelligence in smart manufacturing. International Journal of Production Research, 1–44. https://doi.org/10.1080/00207543.2025.2513574

Romero, C., & Ventura, S. (2020), Educational data mining and learning analytics: An updated survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(3), e1355.

Salem, M., Shaalan, K. (2025), Unlocking the power of machine learning in E-learning: A comprehensive review of predictive models for student performance and engagement. Educ Inf Technol, 30, 19027–19050. https://doi.org/10.1007/s10639-025-13526-4

Shaporeva, A., Kopnova, O., Shmigirilova, I., Kukharenko, Y., Aitymova, A. (2022), Development of comprehensive decision support tools in distance learning quality management processes. Eastern-European Journal of Enterprise Technologies, 4(3), 43–50. https://doi.org/10.15587/1729-4061.2022.263285

Tang, Z., Jain, A., & Colina, F. E. (2024), A Comparative Study of Machine Learning Techniques for College Student Success Prediction. Journal of Higher Education Theory and Practice, 24(1). https://doi.org/10.33423/jhetp.v24i1.6764

Villegas-Ch, W., Gutierrez, R., García-Ortiz, J. et al. (2025), Explainable educational assistant integrated in Moodle: automated semantic assessment and adaptive tutoring based on NLP and XAI. Discov Artif Intell, 5, 191.

