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EXPLAINABLE ARTIFICIAL INTELLIGENCE IN EDUCATION: TRANSFORMING TEACHING AND LEARNING - A REVIEW

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Abstract. Explainable Artificial Intelligence (XAI) has emerged as a critical area of focus in education, where transparency and trust in AI-driven decisions are essential. This systematic review analyzes the role of XAI in predicting and enhancing student performance in educational settings. A total of 102 peer-reviewed studies published between 2015 and 2025 were examined to evaluate the use of machine learning models and explainability techniques in student performance prediction. The review highlights the most commonly applied XAI methods, such as LIME and SHAP, and assesses their effectiveness in improving interpretability without significantly compromising accuracy. Key findings indicate that integrating XAI into educational systems fosters trust among stakeholders, enables more informed decision-making, and supports early identification of at-risk students. Challenges associated with model complexity, data quality, and ethical considerations are also discussed. This review provides comprehensive insights into current XAI applications in education and identifies future research opportunities aimed at developing transparent and equitable AI-based student support systems.
Keywords: Performance Prediction of Student, Explainable Artificial Intelligence (XAI), Education, Machine Learning, Systematic Literature Review.

1. INTRODUCTION

Machine Learning (ML) and Artificial Intelligence (AI) have revolutionized numerous sectors, including education. AI system integration in educational environments offers unprecedented opportunities for personalized learning, performance prediction, and administrative efficiency [7, 60]. The capabilities of AI to analyze vast amounts of educational data enable the discovery of patterns and insights that can improve learning and teaching experiences [52].However, the ”black-box” nature of many AI models poses significant challenges, particularly in critical domains like education where understanding and trust in AI decisions are paramount [18, 68, 97]. Stakeholders often require explanations for the predictions and recommendations made by AI systems to ensure they are impartial, equitable, and in line with learning objectives.Explainable perspective of Artificial Intelligence (XAI) seeks to address these challenges by making AI systems more transparent, interpretable, and trustworthy [72]. In education, XAI can enhance stakeholders' understanding of predictive models used for student performance, dropout prediction, and personalized learning paths [13, 60]. It enables educators tohave a clear perspective into the factors influencing student outcomes, allowing for timely interventions and support [34].
This review aims to provide a comprehensive analysis of XAI applications in education, focusing on predicting and enhancing student performance. By systematically examining existing literature, we identify current methodologies, evaluate their effectiveness, and highlight areas requiring further research.

1.1 Research Objective

The primary objectives of this review are:

1. To critically analyze the application of XAI in educational contexts, specifically in student performance prediction.
2. To identify the machine learning models and XAI techniques commonly used.
3. To assess the impact of XAI on enhancing interpretability and trustworthiness in educational AI systems.
4. To highlight challenges and propose future research directions

2.0 METHODOLOGY USED FOR REVIEW PROCESS

This section describes concisely the detail methodology/procedures employed so that anyone wishing to replicate the trial can do so and obtain comparable results. Provide sufficient detail so as to remove any possible ambiguities with respect to design, treatments, measurements, analysis, etc. Where methods employed are commonly known in a given field details should be omitted and the reference given instead. Modifications to known methodology must however be clearly described and explained.

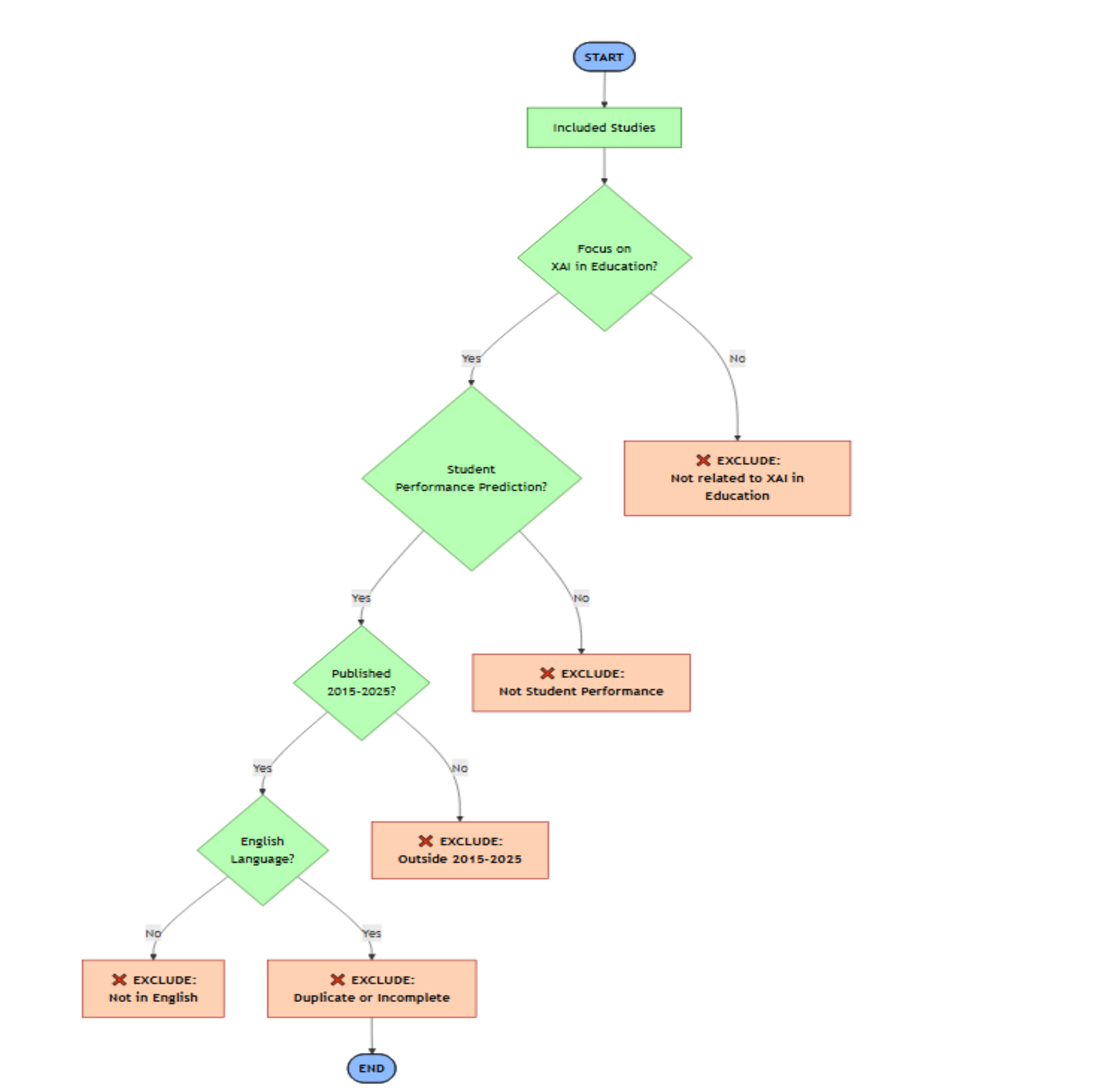

Figure 1 : Document Selection Process

2.1 Inclusion and Exclusion Criteria

As illustrated in Figure 1, the flowchart outlines the inclusion criteria for studies focusing on explainable AI in education, highlighting key decision points in the evaluation process. We included studies that:

- Emphasis on the application of XAI in education.
- Involved performance of students using machine learning models.
- Were published in peer-reviewed journals or reputable conferences between 2015 and 2025.

We excluded studies that:

- Did not specifically address explain ability in AI models.
- Were not available in English.
- Were duplicates or incomplete.

3 LITERATURE REVIEW

Artificial Intelligence (AI) into education has attracted substantial attention in recent years, prompting numerous studies that examine its influence on teaching methodologies, student performance, and overall educational outcomes. The results of numerous research studies are combined in present study to get a thorough picture of the status of AI applications today. in education, the challenges encountered, and the future directions for research.

3.1 Explainable AI in Education

Explainable AI (XAI) has become a pivotal area of research within the educational sector, where transparency and trust are essential. Chaushi [34] underscores the significance of XAI in educational settings, highlighting the necessity for developing new competencies and skills to facilitate effective interaction with AI systems. The study addresses challenges such as algorithmic complexity and the demand for transparency, suggesting solutions like human-AI collaboration and the implementation of ethical frameworks.

Building on this, Haque [48] offers a thorough review of XAI from the end-user's perspective. While XAI aims to mitigate the gap between complex AI models and users, Haque identifies a persistent need for research focused on real-world applications and enhancing end-user engagement. This gap indicates that further work is necessary to build user trust and improve understanding of AI systems. Rajpura et al. [83] explore the application of XAI techniques to Brain-Computer Interfaces (BCI), emphasizing the importance of explain ability for all stakeholders involved. They discuss the inherent trade-off between explainability and accuracy and propose a comprehensive framework to navigate these challenges. This work sparks discussions on the need to establish standardized explanations for BCI technologies.

Paper [66] emphasizes the significance of evaluating educational data to enhance student performance and institutional efficacy in their evaluation of data mining approaches in educational contexts, providing useful insights for educators and policymakers. In a systematic review, [73] look at different automated learning methods for academic performance prediction, highlighting how it would improve educational management and raise educational quality.

3.2 Predicting Student's Performance: ML Techniques

Machine learning (ML) has become vital in predicting student performance. Yang [99] highlights neural networks as highly reliable for forecasting academic success. Adejo and Connolly [3] show that combining multiple data sources with ensemble techniques enhances prediction accuracy and supports effective educational policies. Nadar and Vijayarani [74] introduce a modified XGBoost model using stream-based analysis, outperforming traditional methods and enabling early identification of at-risk students.

Figure 2 illustrates the taxonomy of Explainable Artificial Intelligence (XAI) in Education, outlining six key areas—Applications, Methodologies, Challenges, Future Directions, Stakeholder Insights, and Other Domains—offering a clear overview of XAI research and its educational impact.

Abbas et al. [1] and Sharma et al. [26] demonstrate that AI-driven personalized learning and intelligent tutoring systems improve engagement, inclusivity, and learning outcomes, promoting adaptive education for diverse learners.

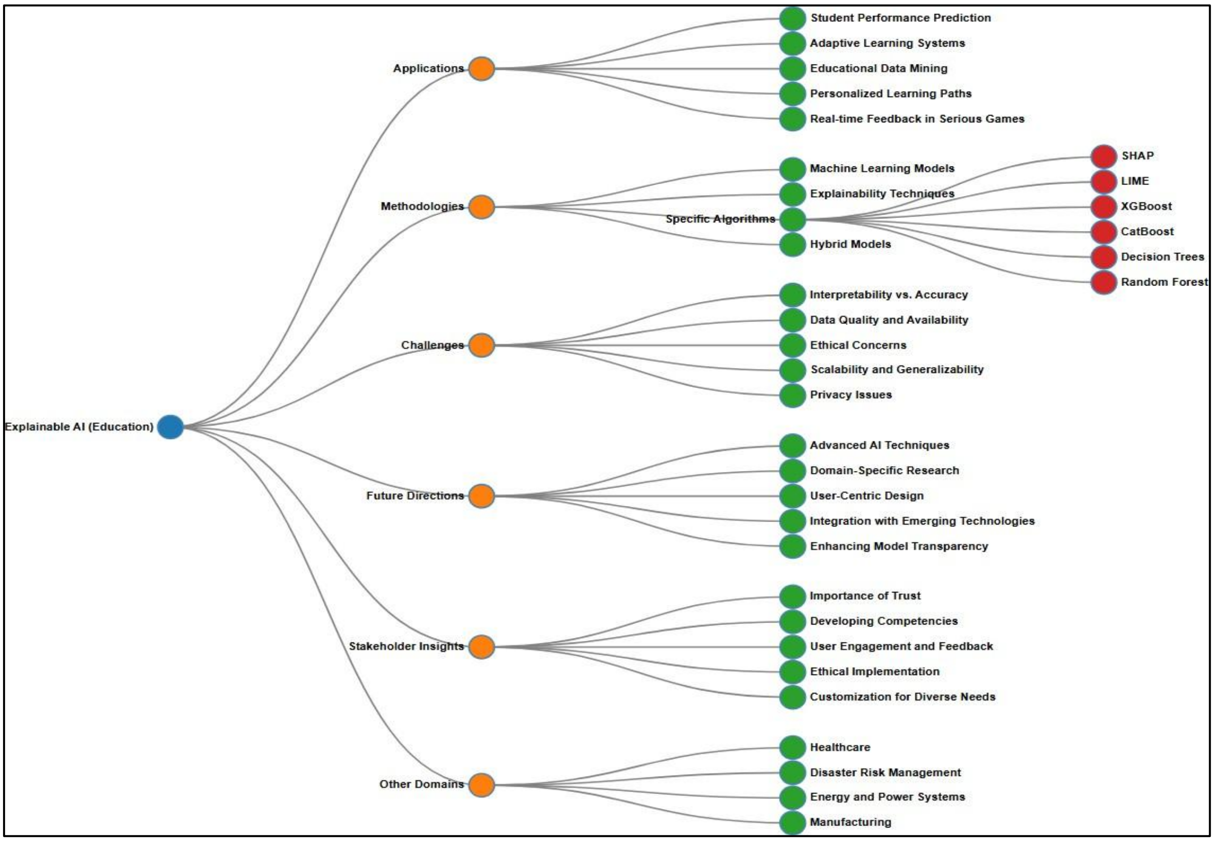

Figure 2: The XAI Landscape in Education

3.3 Addressing Challenges and Ethical Considerations in AI Implementation

There are various obstacles to overcome when integrating AI into the classroom. In order to better assist students and teachers in accomplishing educational objectives, Asiah et al. [24] stress the necessity of enhanced data quality and reliable forecasting techniques. Selecting influential variables is crucial for effective AI implementation.

Ali et al. [17] delve into the challenges associated with AI applications in education, offering insights for educators and policymakers to enhance AI tool usage, such as ChatGPT. They categorize AI challenges into five dimensions: user, operational, environmental, technological, and ethical. The study provides recommendations for leveraging AI as an effective teaching aid.

Fiok and Magana [43] highlight the importance of XAI methods in education to mitigate risks and build trust in human-AI interactions.

3.4 Impact of AI on Educational Strategies and Stakeholder Engagement

AI is also transforming educational strategies and stakeholder engagement. Muthuprasad et al. [67] discuss the use of AI for monitoring student performance, highlighting how real-time feedback and personalized learning experiences can significantly enhance educational outcomes.

Gallastegui et al. [44] examine the strategic transformation in higher education driven by digitalization and evolving expectations. They explore the role of AI-based predictive models in improving the student experience and satisfaction, achieving prediction accuracies of up to 95.7 Additionally, Bhutoria et al. [30] analyze the use of AI for personalization in education across the United States, China, and India. Their research demonstrates that AI effectively caters to specific learning requirements and habits, enhancing and customizing educational content to meet individual needs.

3.5 Analysis of Educational Data and Learning

Data Mining of Educational data and analytics are important for predicting student performance and refining educational strategies. Namoun and Alshanqiti [75] systematically review intelligent techniques used to predict academic performance based on learning outcomes. Their findings show that regression and supervised models of machine learning are commonly used, with significant predictors such as online learning activities, term assessment grades, and academic emotions. Dhankhar et al. [39] stress the importance of identifying techniques and attributes that enhance prediction accuracy. They assess the metrics used in educational data mining, contributing to the enhancement of more impressive prediction models.

Lopez-Zambrano et al. [64] review research on applying data mining approaches to predict student learning success early on. They suggested that numerous studies concentrate on online and traditional learning systems, utilizing typical predictive algorithms such as J48, SVM, Naive Bayes, Random Forest and different regression techniques.

3.6 Future Opportunities and Research Directions

Several findings suggest promising future research.

[77] recommendations to strengthen AI's role in education. Ahmad et al. [9] offer a review of AI applications in education, identifying future opportunities and current limitations. Their bibliometric analysis of research trends from 2014 to 2019 provides a foundation for future investigations.

Afrin et al. [5] focus on using counterfactual explanations to improve the prediction of student success, addressing the explainability challenges in AI models. Their findings suggest that modifications in social media usage can alter predicted outcomes from failing to passing, offering valuable insights for educators seeking to support student success.

Oppong and Sai [79] undertake a systematic literature evaluation on predicting student performance using ML techniques. They identified that neural networks are commonly used classifiers for predicting academic performance and guided for further analysis to improve prediction accuracy.

3.7 Research Gap Identification

AI integration in education enhances learning, personalization, and engagement but raises concerns about ethics, privacy, and transparency. Explainable AI (XAI) helps build trust and accountability in these systems. Future research should focus on standardized evaluation methods, benchmark datasets, and ethical considerations to ensure effective and responsible AI adoption. The review also highlights key gaps in current research.

As shown in Figure 3, the primary gaps include:

1. Limited focus on integrating both academic and non- academic features in prediction models.
2. Challenges in model scalability across varying dataset sizes.
3. Data imbalance issues affecting model performance.

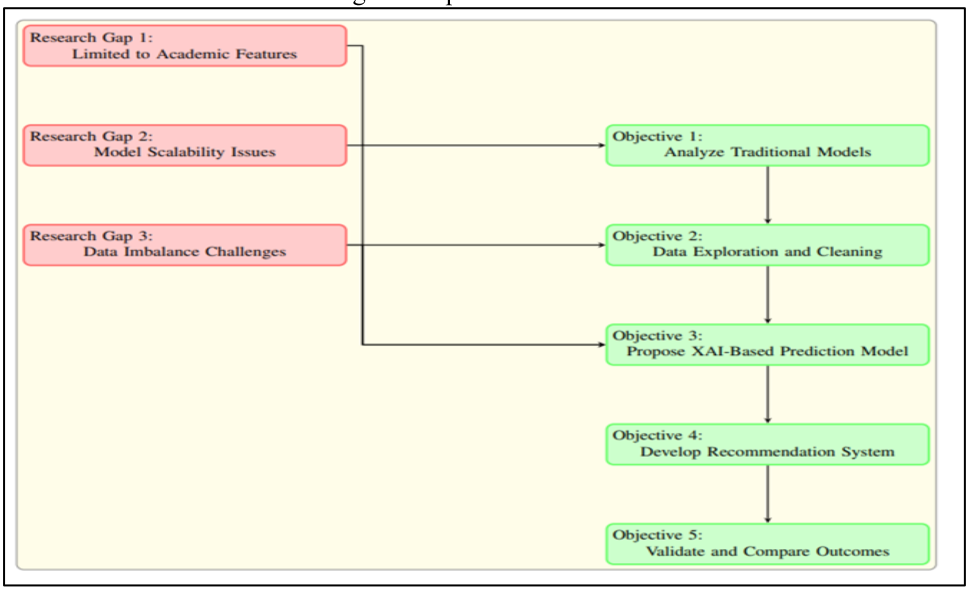

Figure 3: Research Gaps Identification

4. EXPLAINABLE AI IN EDUCATION

Explainable AI has become an essential aspect of educational AI systems, addressing the need for transparency and interpretability [9, 18, 60]. Educators, students, and policymakers do require AI models which are easy to Understand to make informed decisions and trust the AI's outputs [72, 97].

4.1 Importance of Explainability

The explainable aspects of AI models in education is important and crucial for several reasons:

• Trust and Acceptance: Transparent models build trust among users, leading to higher acceptance rates [37, 82]. Teachers and students will refer AI based recommendations when they understand the reasoning behind them [43].

• Improved Decision-Making: Understanding model predictions helps educators tailor interventions [59, 60]. For instance, identifying specific factors affecting a student's performance allows for personalized support [91].

• Ethical Considerations: Explainability addresses concerns related to fairness and bias [34]. Transparent models help detect and mitigate biases that may disadvantage certain student groups [54].

• Regulatory Compliance: In some regions, regulations require AI systems to provide explanations [98]. The General Data Protection Law the European Union's (GDPR) places a strong emphasis on the right to explanation.

4.2 Frameworks and Models

Several frameworks for integrating XAI into educational systems have been proposed. Khosravi et al. [60] introduced the XAI-ED framework, focusing on stakeholders, benefits, explanation approaches, AI model classes, human-centered designs, and potential pitfalls in educational AI tools. This framework emphasizes the importance of considering the needs of different users in the educational ecosystem. Furthermore, Mohseni et al. [72] presented a multidisciplinary review and framework for XAI systems, emphasizing the significance of user-centered approaches. They grouped XAI design goals and evaluation methodologies and assigned them to various user groups.

5 MODELS OF MACHINE LEARNING USED IN PERFORMANCE PREDICTION OF STUDENTS

As presented in Table 1, the analysis of various machine learning studies highlights key trends in predicting student performance. Various algorithms of ML methods are used for student performance prediction. The selection of models often balances predictive accuracy with interpretability [9, 55].

5.1 Decision Tree

Another popular approach is Decision trees, which are in use due to their inherent interpretability [13, 37, 80]. They provide a visual representation of decisions, making it easier for educators to understand the factors influencing predictions. Studies like [85] have effectively used decision trees to predict student performance.

5.2 Random Forest

Ensemble methodology that uses multiple decision trees with Random Forest to improve predictive performance while maintaining some level of interpretability [22, 27]. For example, Alsariera et al. [22] demonstrated the effeciveness of Random Forest in predicting student performance with high accuracy.

5.3 Support Vector Machines (SVM)

SVMs are deployed for classification tasks, although it was not quite explainable than decision trees [13, 28]. They are effective in handling high data dimensionality, as mentioned in [52].

5.4 Ensemble Models

Ensemble techniques use many models to improve forecast accuracy. Techniques such as XGBoost and CatBoost have been successful in forecasting student performance [57, 84, 89]. Sahlaouiet al. [89] produced considerable improvements by employing ensemble methods.

5.5 Regression Algorithms

Regression approaches, like logistic and linear regression, are in use to predict continuous or binary student performance outcomes [13, 60–85]. Logistic regression found super useful for binary classification applications, like predicting pass/fail results [51]

5.6 Deep Learning Models

As per Table 2, results show several studies on deep learning strategies for student performance provide crucial insights. Deep learning approaches, such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have gained popularity due to their ability to handle complex data structures [20].

6 Explainable AI Techniques Employed

6.1 Model-Agnostic Methods

6.1.1 LIME (Local Interpretable Model-Agnostic Explanations)

LIME explains individual predictions by approximating the black-box model locally with an interpret able model [4, 50]. It has been vastly used due to its simplicity and effectiveness in providing local explanations [61].

6.1.2 SHAP (Shapley Additive explanations)

SHAP offers both global and local explanations by using Shapley values using cooperative game theory to indicate feature importance [78,89]. It unifies several methods and is appreciated for its consistency and theoretical foundation.

6.2 Model-Specific Methods

6.2.1 Feature Importance Analysis

Some methods such as permutation importance and Gini important can assist determine which features contribute the most to predictions [37, 55]. This aids in the detection of crucial elements influencing student performance [83].

6.2.2 Rule-Based Explanations

Extracting rules from models like decision trees or decision rules provides an interpretable representation of process for decision-making [56]. This is beneficial for stakeholders who prefer clear and concise explanations.

6.3 Visual Explanations

Some Visualization Techniques such as partial dependency plots, conditional expectation plots, and heat maps help grasp the relationship between features and predictions. [31, 60]. These tools basically enhance the Understanding of complex models.

Table 1: Machine learning studies highlights key trends in predicting performance of students.

Citation	Paper Title	ML Methods	Key Findings
[57]	CatBoost - An Ensemble Machine Learning Modelfor Classification and Prediction of Student Academic Performance	CatBoost, Hyperparameter Optimization, SMOTE	CatBoost model achieved a superior accuracy of 92.27% over standard models. SHAP values increasedmodel transparency for educational prediction. SMOTE and hyper-parameter optimization enhanced model performance.
[79]	Predicting Performance of the Students Using Machine Learning Algorithms: A Review	Feature selection, Supervised learning	59% of the studies employed feature selection methods to improve model performance. 87% of the algorithms used were supervised learning.
[44]	Optimization of the Educational Experience in Higher Education Using Predictive Artificial Intelligence Models	Experimental machine learning techniques, Predictive models	Predictive models achieved 95.7% accuracy in predicting student satisfaction. There is a significant positive correlation between teaching personalization and student sat isfaction.
[82]	Explainable Machine Learning Prediction for the Academic Performance of Deaf Scholars	ExtraTrees, Random Forest, XGBoost	A stacked model with XGBoost,ExtraTrees, and Random Forest achieved 92.99% accuracy. Explainable AI methods LIME andSHAP provided insights into crucial criterion like communicationmode and early intervention.
[50]	This is a ML and Explainable AI Approachfor Predicting Secondary School Student Performance	K-Nearest Neighbors(KNN), Logistic Regression, Naive Bayes Algorithm, Support Vector Machine algorithm (SVM), XGBoost algorithm	LIME was used to provide model interpretability. Support Vector Machine (SVM) achieved the highest accuracy of 96.89%.
[89]	Predicting and Interpreting Student Performance Using Ensemble Models and Shapley Additive Explanations	Ensemble models, Gridsearch for hyperparameter optimization, Synthetic Minority Oversampling Technique (SMOTE)	SHAP values help interpret which factors most influence student performance. The proposed modelachieves an accuracy of over 98%, a 20.3% improvement compared toprevious models.
[78]	Prediction of Students' Adaptability Using Explainable AI in Educational Machine Learning Models	ALE, Anchors, Counterfactual explanations, LIME, Random Forest, SHAP	Key features influencing adaptability include 'Class Duration' and 'Financial Condition'. Random Forest achieved highest accuracy at 91%.
[40]	Enhancing Academic Outcomes through an Adaptive Learning Framework Utilizing a Novel Machine Learning-Based Performance Prediction Method	Predictive machine learning model	Experimental groups showed higher scores in both computer science and French. Predictive model demonstrated 90% accuracy.
[71]	A Systematic Literature Re- view of Explainable AI for Software Engineering	Classic ML models	Lack of standard evaluation metrics for XAI methods. Software maintenance and defect prediction have the highest share of SE stages and tasks studied. XAI methods are mainly applied to classic ML mod- els.

[35]	Evaluation of students' performance during the academic period using the XG-Boost Classifier-Enhanced AEO hybrid model	Decision Tree Classifier, K Neighbors Classifier, MLP Classifier, Random Forest Classifier, XG-Boost Classifier	Enhanced AEO + XG-Boost hybrid achieves high accuracy and F1- score. SVM-SMOTE technique improves model performance. Out of all the evaluated approaches, XG-Boost performs the best.

Table 2: Various evaluation metrics used in the literature review highlight metrics trends in model used.

Citation	Title	Metrics
[47]	Utilizing Explainable AI to Enhance Real-time Prediction of Student Performance in Educational Serious Games	balanced accuracy
[99]	Predicting Performance o f Student Using Artificial Neural Networks	Accuracy, Reliability
[49]	A Practical Model for Educators to Predict Student Performancein K-12 Education using ML Techniques	Accuracy
[69]	On the Use of eXplainable Artificial Intelligence to EvaluateSchool Dropout	Explanatory evaluation metrics
[38]	Evaluation Metrics in Explainable Artificial Intelligence (XAI)	Categorization of evaluation methods, Mapping of tools to metrics
[65]	Explainable Artificial Intelligence for Academic Performance Prediction. An Experimental Study on the Impact of Accuracy and Simplicity of Decision Trees on Causability and Fairness Perceptions	Fairness Perceptions
[79]	Predicting Performance of Students Using Machine Learning Algorithms: A Review	Accuracy
[74]	Enhancing performance of student prediction through stream-based analysis dataset using modified xgboost algorithm	accuracy, precision, sensitivity, F1-score
[44]	Optimization of the Educational Experience in Higher EducationUsing Predictive Artificial Intelligence Models	Accuracy
82]	Explainable Machine Learning Prediction for the Academic Performance of Deaf Scholars	Accuracy
[58]	Student Performance Prediction: A Co-Evolutionary Hybrid Intelligence model	Accuracy, Precision, Recall, F1 Score
[28]	Predicting performance of student's using machine learning methods: A systematic literature review	accuracy
[63]	Trustworthy and Explainability of AI for Learning Analytics	Accuracy, Stability
[33]	Academic Performance Prediction Using ML techniques: AComprehensive & Systematic Review	Accuracy
[53]	Artificial Intelligence for Assessment and Feedback to EnhanceStudent Success in Higher Education	Performance metrics
[78]	Prediction of Students' Adaptability Using Explainable AI inEducational Machine Learning Models	Accuracy, Precision, Recall, F1-score
[70]	Exploring Explainable Artificial Intelligence Technologies: Approaches, Challenges, and Applications	standardized evaluation metrics

7 Evaluation Metrics

Recent studies highlight a growing interest in applying AI and ML models for predicting student performance. A review of 38 studies shows a wide range of evaluation metrics used to assess model performance and reliability.

7.1Predominant Evaluation Metrics

Accuracy is the most widely used metric, appearing in most studies. However, it is often complemented with **precision, recall,** and **F1-score** to provide a more balanced evaluation, especially for imbalanced datasets. **Balanced Accuracy** and **AUC** are used to handle class imbalance, while **RMSE** and **MAE** are common in regression tasks for measuring prediction error.

7.2 Emerging and Specialized Metrics

Recent research incorporates **explainability** and **fairness** metrics to evaluate ethical and interpretive aspects of AI models. Metrics related to **generalization capacity** and **stability** are also gaining importance to ensure model robustness across varied datasets.

7.3 Performance Optimization Metrics

Metrics like **execution time** and **efficiency** are used to ensure models are not only accurate but also computationally feasible for real-time educational applications.

7.4 Comprehensive and Multi-Faceted Evaluations

Many studies now employ **multi-metric evaluation frameworks**, combining accuracy, precision, recall, and F1-score to provide a holistic assessment and enable fair comparison among different models.

7.5 Need for Standardization for Evaluation Metrics

Despite progress, there is still no standardized approach for including **ethical, interpretability,** and **user-centric metrics**. Future research should aim to standardize evaluation frameworks to ensure models are **accurate, fair, transparent,** and **applicable** across diverse educational contexts.
The use of **Explainable AI (XAI)** has improved both the **accuracy** and **interpretability** of student performance prediction models.

8 Impact on Student Performance Prediction

8.1 Enhanced Predictive Accuracy

Integrating ensemble models with XAI methods significantly boosts accuracy. Studies achieved up to **98% accuracy** (Sahlaoui et al. [89]) and **92.27%** (Joshi et al. [57]) using models like **CatBoost** and **SHAP**, improving both prediction and explanation of outcomes.

8.2 Improved Interpretability

XAI tools such as **LIME** and **SHAP** help educators understand key factors affecting performance, increasing transparency and supporting data-driven decisions. These techniques bridge the gap between complex models and user understanding.

8.3 Case Studies:

8.3.1 Predicting At-Risk Students

XAI-based models enable **early identification** of at-risk students, allowing timely interventions to enhance retention. Hybrid regression and classification models help identify influential factors (Alshanqiti & Namoun [23]).

8.3.2 Personalized Learning Paths

XAI supports **personalized learning** by revealing each student's strengths and weaknesses. Studies show improved engagement and performance through adaptive educational tools integrating XAI (Khosravi et al. [60]).

9 Challenges Identified

Despite the advancements, several challenges persist in integrating XAI into educational practice.

9.1 Balancing Accuracy and Interpretability

High-performing models for example DNNs are often less interpretable. There's a trade-off between model complexity and explainability [8, 13, 43]. Development of models which are accurate and interpretable remains a challenge.

9.2 Data Quality and Availability

Lack of standardized datasets and issues with data quality hinder model development and comparability across studies [12, 77, 100]. Issues such as missing data, imbalanced classes, and inconsistent data collection methods affect model performance [76].

9.3 Evaluation Metrics

Reliable metrics for evaluation that assess both the predictive performance, and the quality of explanations provided by XAI models [38, 72, 97]. Existing metrics often focus on accuracy while neglecting interpretability [88].

9.4 User Trust and Acceptance

Ensuring stakeholders trust AI predictions and explanations remains a challenge. Factors affecting trust include the clarity of explanations and alignment with user expectations [4, 34, 86]. Studies emphasize the importance of involving users in the design and evaluation of XAI systems [72].

9.5 Ethical Considerations

Privacy, fairness, and bias in AI models are key concerns in educational contexts. XAI can help identify and mitigate biases but have few questions about the appropriate use of sensitive data [19, 43]. To ensure that AI is used responsibly in education, ethical rules and frameworks must be established.

10. Developing a Comprehensive Prediction Model – Objectives

The comprehensive prediction model is rather essential for accurately assessing student performance. By addressing the limitations of traditional approaches and incorporating a broader range of influencing factors, this model aims to enhance educational outcomes. The integration of both academic and non-academic attributes will facilitate more effective interventions and support tailored to individual student needs.

- Objective 1: Analyze traditional models to identify limitations in considering only academic features.
- Objective 2: Integrate non-academic factors such as socio-economic background, attendance, and engagement metrics to provide a holistic prediction. Prepare a custom student dataset for such holistic approach.
- Objective 3: Scalability in machine learning algorithms suitable for varying dataset sizes, including transfer learning techniques.
- Objective 4: Apply advanced data balancing methods like SMOTE and cost-sensitive learning to address data imbalance issues.

10.1 Implementing Explainable Artificial Intelligence (XAI)

To ensure transparency and trust in the prediction model, XAI techniques will be incorporated. This will allow educators and stakeholders to have a clear understanding of the decision-making process for the model, fostering better decision- making and interventions.

10.2 Designing a Recommendation System
Building on the prediction model, a recommendation system will be developed to provide personalized strategies so that students can improve their performance. This system will leverage the insights generated by the prediction model to offer actionable advice.
10.3 Validation and Comparison
The proposed framework will be rigorously tested against existing models using standardized datasets. Performance metrics will include accuracy, scalability, and explain Such a dataset is crucial for capturing the multifaceted nature of student performance, as it allows for a comprehensive analysis that reflects the diverse influences on learning outcomes. By including variables that address students' environments and personal circumstances, the model can better identify at-risk students and tailor interventions more effectively.
10.4 Integration of Ethical Considerations
Ensuring fairness and mitigating biases in the model is paramount. The research will incorporate ethical guidelines and fairness metrics to develop an unbiased and equitable prediction system.

11 Proposed Architecture Model
As described in the figure 5 we outline the architecture model designed to develop a comprehensive prediction model that integrates both academic and non-academic factors. The model is structured around four primary objectives, each addressing specific aspects essential for accurate and holistic predictions.
Objective 1: Analyze Traditional Models
Traditional prediction models are often based solely on features based on academic domain such as grades and test scores. This objective involves a critical analysis of these models to identify their limitations, particularly in their inability to account for a broader range of influencing factors.
Objective 2: Integrate Non-Academic Factors
To provide a more holistic prediction, it is imperative to incorporate non-academic factors. These include socio-economic background, attendance records, and engagement metrics. By integrating these variables, this model seeks to provide a more complete picture of the predictors that influence the outcome. This entails creating a bespoke dataset for the student prediction system.
Objective 3: Scalability in machine learning algorithms
Scalability is a key consideration for handling varying dataset sizes. This objective focuses on implementing various algorithms of machine learning that can efficiently scale, including leveraging transfer techniques of Learning to enhance model performance across different datasets.
Objective 4: Apply Advanced Data Balancing Methods
Data inconsistency can significantly influence prediction outcomes. To solve this, advanced data balancing approaches such as the Synthetic Minority Oversampling Technique (SMOTE) and cost-sensitive learning are used. These strategies help to reduce the consequences of imbalanced datasets, resulting in more trustworthy and unbiased predictions.
11.1 Advancing XAI Techniques
Further advancements in XAI will be pursued to enhance the interpretability of complex models. This includes exploring hybrid XAI approaches that combine multiple explanation methods for richer insights.
11.2 Developing a User-Centered Design
Engaging educators and students through user studies will inform the design and functionality of the prediction and recommendation systems, ensuring they effectively meet user needs and enhance trust in AI-driven decisions.

12 CONCLUSION

Explainable Artificial Intelligence holds significant promise for enhancing educational outcomes by providing transparent, interpretable, and accurate models for student performance prediction. While progress has been made, challenges remain in balancing accuracy with explainability, improving data quality, and fostering user trust. Continued research and collaboration among educators, AI practitioners, and policymakers are essential to realize the full potential of XAI in education.
By solving the highlighted obstacles and emphasizing user-centered design, ethical considerations, and sophisticated XAI approaches, we may create AI systems that accurately predict student performance and also provide valuable insights to educators and learners. Furthermore, the incorporation of non-academic characteristics into predictive models will help to provide a more complete picture of student needs and obstacles, enabling for targeted interventions to improve learning experiences.
As we move forward, we must involve stakeholders at all levels to confirm that XAI tools development is in accordance with the practical situations in which they will be used. Training and support for educators in using these technologies will be vital to maximizing their benefits. Ultimately, fostering a culture of collaboration and innovation will empower institutions to leverage AI effectively, driving improvements in educational practices and outcomes for diverse student populations.
In conclusion, the journey toward fully realizing the potential of Explainable AI in education is ongoing. By prioritizing transparency, inclusivity, and continuous feedback, we can build a smarter path for smarter, more responsive educational environments that not only predict but also enhance student success.

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