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A Comprehensive Survey of Data-Driven Student Performance Prediction from Educational Data Mining to Explainable Artificial Intelligence

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Abstract—Student performance prediction has become an important research area in digital education, focusing on analyzing academic, behavioral, and interaction data to improve learning outcomes and institutional decision-making. Artificial Intelligence, Educational Data Mining, Deep Learning, and Explainable AI techniques enable early identification of at-risk students while supporting personalized and adaptive learning environments. Existing studies apply machine learning models, neural networks, learning analytics, and explainable frameworks to achieve accurate prediction and effective academic support. This survey paper analyzes research contributions across major subtopics including Educational Data Mining, Machine Learning, Deep Learning, Peer Learning Analytics, AI-driven Feedback Systems, and Explainable AI by reviewing studies published between 2022 and 2026. The survey examines methodological trends, datasets, evaluation metrics, and performance outcomes reported in recent literature. However, challenges such as limited interpretability, scalability issues, real-time data integration limitations, and lack of cross-institution generalization still persist, highlighting the need for hybrid, transparent, and learner-centered predictive frameworks for intelligent educational systems.

Keywords—Artificial Intelligence, Deep Learning, Educational Data Mining, Explainable AI, Learning Analytics, Machine Learning, Student Performance Prediction

I. INTRODUCTION

The rapid growth of digital education platforms has generated massive volumes of educational data, enabling the application of Artificial Intelligence (AI) and Educational Data Mining (EDM) to enhance learning outcomes [1]. Student performance prediction has emerged as an important research area that analyzes academic, behavioral, and interaction data to understand learning patterns and support data-driven educational decision-making [2]. Modern learning environments such as Learning Management Systems (LMS), online courses, and intelligent tutoring systems continuously collect learner data, allowing researchers to develop predictive models that improve academic success and personalized learning experiences [3]. Learning analytics techniques further support institutional planning and adaptive learning strategies through continuous monitoring of learner activities [4].

Despite technological advancements, educational institutions still face challenges in identifying students at risk of poor academic performance or dropout at an early stage [5]. Traditional evaluation methods mainly rely on final examination results and static academic records, which fail to capture dynamic learning behaviors and engagement patterns [6]. Collaborative learning interactions and peer participation also influence academic outcomes but remain underutilized in many prediction frameworks [7]. Furthermore, many AI-based prediction systems operate as black-box models, limiting interpretability and reducing educators' trust in automated recommendations [8]. These limitations highlight the need for intelligent systems capable of providing transparent explanations and actionable feedback for timely academic intervention [9].

Existing research has explored machine learning algorithms for classification, regression, and clustering tasks in student performance prediction [10]. Deep learning approaches, including neural networks and hybrid architectures, have demonstrated improved prediction accuracy using large-scale educational datasets [11]. Educational Data Mining techniques enable pattern discovery and knowledge extraction from student interaction logs [12]. Recent studies incorporate explainable AI methods to improve model transparency and decision interpretability [13]. Peer learning analytics and collaborative behavior modeling further enhance understanding of learner engagement and academic performance [14]. AI-driven feedback systems support personalized recommendations and adaptive learning pathways [15].

Several studies report strong predictive performance using ensemble models and data fusion strategies across multiple learning environments [16]. Learning analytics dashboards assist educators in monitoring progress and implementing early interventions [17]. Hybrid predictive frameworks combining EDM, machine learning, and deep learning improve robustness and generalization capability [18]. However, challenges such as dataset dependency, scalability issues, and limited cross-institution validation still persist [19]. Real-time learning analytics integration remains an open research problem in intelligent educational systems [20]. Ethical concerns related to fairness, privacy, and transparency also require careful consideration when deploying AI-based educational solutions [21]. Future research emphasizes learner-centered predictive models capable of adaptive decision support [22]. Therefore, integrating Educational Data Mining, Deep Learning, and Explainable AI provides a comprehensive direction for developing interpretable, scalable, and intelligent student performance prediction systems [23].

II. BACKGROUND STUDY

The background study presents a comprehensive review of existing research related to student performance prediction using Educational Data Mining, Machine Learning, Deep Learning, Learning Analytics, and Explainable AI techniques. It highlights how different predictive models are used to analyze academic, behavioral, and LMS-based data for identifying student performance levels and at-risk learners. This section also discusses the key findings, limitations, and research gaps in current approaches to support the need for improved, scalable, and interpretable prediction systems.

a. Existing Research on Student Performance Prediction

Chen et al. (2023) [1] proposed a student performance prediction model using educational data mining techniques to analyze learning behavior patterns. Machine learning algorithms such as Random Forest and Decision Tree were applied on educational datasets collected from academic records and online activities, achieving high prediction accuracy. The study showed improved prediction performance but faced limitations related to dataset generalization and institutional dependency.

Pallathadka et al. (2023) [2] investigated classification and prediction of student academic performance using multiple machine learning algorithms. Methods including SVM, Naïve Bayes, and Logistic Regression were tested on student academic datasets, producing competitive accuracy levels across models. The limitation lies in limited feature diversity and absence of real-time learning analytics integration.

Alhazmi & Sheneamer (2023) [3] focused on early prediction of higher education student performance to support timely intervention strategies. The research applied supervised learning models on university academic datasets to identify at-risk students with strong predictive accuracy. However, the model performance depends heavily on data completeness and lacks cross-institution validation.

Baig et al. (2023) [4] introduced an integrated machine learning framework combining multiple algorithms to predict student performance levels. Ensemble learning techniques were applied to academic datasets, achieving improved classification accuracy compared to single models. The limitation includes increased computational complexity and requirement of large training datasets.

Karale et al. (2022) [5] developed an AI and ML-based system for predicting student performance using academic and behavioral attributes. Algorithms such as KNN, Decision Tree, and ANN were used on institutional datasets, providing satisfactory prediction accuracy. The study highlighted challenges related to small dataset size and limited scalability.

Baashar et al. (2022) [6] proposed an Artificial Neural Network model for predicting academic performance based on student learning indicators. The ANN model was trained on educational datasets containing demographic and academic variables, achieving high predictive accuracy. The main limitation involves model interpretability and dependency on large volumes of labeled data.

Khan et al. (2023) [7] utilized LMS activity logs to predict student academic outcomes through machine learning techniques. Models such as Gradient

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Boosting and Random Forest analyzed interaction datasets extracted from learning management systems, resulting in accurate performance prediction. Limitations include privacy concerns and dependence on continuous LMS usage data.

Jang et al. (2022) [8] presented an early prediction framework using machine learning integrated with Explainable AI techniques. The study used academic and behavioral datasets to provide interpretable predictions with improved transparency and accuracy. However, computational overhead and complexity of explainability methods remain challenges.

Abunasser et al. (2022) [9] explored prediction of instructor performance using machine learning and deep learning models. Classification algorithms were applied to educational evaluation datasets, achieving reliable prediction accuracy for teaching performance assessment. The limitation is restricted applicability to institutional evaluation data only.

Munir et al. (2022) [10] conducted a systematic review of artificial intelligence and machine learning applications in digital education environments. Various AI-based predictive models and educational datasets were analyzed to evaluate trends and effectiveness in performance prediction. The study identified challenges including data heterogeneity and lack of standardized evaluation metrics.

Fleckenstein et al. (2023) [11] performed a meta-analysis examining automated feedback systems and their influence on student academic performance. Statistical analysis methods were used across multiple educational datasets, demonstrating positive impacts on learning outcomes. Limitations include variability in feedback systems and differences in study contexts.

Feng et al. (2022) [12] analyzed student academic performance using educational data mining techniques combined with predictive modeling approaches. Algorithms such as DecisionTrees and Neural Networks were applied on student academic datasets, achieving strong prediction accuracy. The study noted limitations regarding feature selection and model overfitting risks.

Ozyurt et al. (2023) [13] provided a comprehensive analysis of the educational data mining research landscape and future directions. The study reviewed multiple datasets, prediction models, and analytics techniques to highlight emerging trends in student performance prediction. Limitations include dependence on previously published research without experimental validation. Sarker et al. (2024) [14] analyzed academic performance prediction using educational data mining and machine learning algorithms. Classification models were tested on student academic datasets, producing improved accuracy in identifying performance categories. The research emphasized scalability benefits but noted limitations in real-time implementation and dataset diversity.

TABLE 1: LEARNING ANALYTICS AND EXPLAINABLE AI-BASED STUDENT PERFORMANCE STUDIES

Author & Year	Concept	Methods	Limitations	Dataset	Accuracy	Result
Rahman et al. (2022) [15]	Educational data mining to support programming learning through problem-solving behavior analysis	Machine learning models analyzing coding/problem-solving logs	Limited to programming courses and structured tasks	Programming learning activity dataset	~85%	Improved identification of struggling programming students and learning support recommendations
Silva Filho et al. (2023	Application of causal reasoning in educational	Causal inference models and statistical	Requires high-quality causal data	Brazilian secondary education	~82%	Provided deeper understanding of cause–effect

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) [16]	data mining for academic performance analysis	learning techniques	and complex modeling	dataset		relations influencing student performance
Noroozi et al. (2025) [17]	AI and learning analytics to enhance peer learning effectiveness	Learning analytics dashboards and AI-supported collaboration analysis	Difficulties in scaling peer interaction evaluation	Higher education peer learning dataset	~88%	Demonstrated improved collaborative learning outcomes and engagement levels
Moon et al. (2024) [18]	Learning analytics for analyzing peer learning patterns in gamified asynchronous environments	Behavioral analytics and interaction mining	Context-dependent results in gamified platforms	Gamified online learning environment dataset	~84%	Revealed patterns improving student participation and collaboration efficiency
Yu et al. (2026) [19]	Leaderboard feedback system using learning analytics to enhance cognitive engagement	Analytics-driven feedback mechanisms and collaborative learning analysis	May promote competition stress among learners	Online collaborative learning dataset	~90%	Increased student engagement and improved academic performance outcomes
Johora et al. (2025) [20]	Explainable AI model for undergraduate academic performance prediction	Explainable ML models such as SHAP and interpretable classifiers	Computational complexity and interpretability trade-offs	Undergraduate academic dataset	~91%	Produced transparent predictions supporting academic decision-making
Islam et al. (2025) [21]	Integration of Explainable AI with Educational Data Mining for prediction and support systems	Hybrid EDM and XAI frameworks	Requires domain expertise for explanation interpretation	Student academic performance dataset	~92%	Enabled accurate prediction with interpretable insights for early intervention
Chen et al. (2022)	Week-wise early prediction of student performance in	Deep learning with explainable AI techniques	High computational requirement	Virtual Learning Environment (VLE)	~89%	Achieved early risk detection enabling timely academic

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[22]	virtual learning environments		s	dataset		support
Afzaal et al. (2024) [23]	Explainable AI recommendations supporting student self-regulation and feedback	AI-based recommendation systems with informative feedback analysis	Dependence on continuous learner interaction data	Online learning behavioral dataset	~87%	Improved self-regulated learning behavior and academic performance

Table 1 summarizes recent studies integrating Educational Data Mining, Learning Analytics, Artificial Intelligence, and Explainable AI for student performance prediction and learning enhancement. The studies demonstrate improved prediction accuracy, learner engagement, and early identification of at-risk students through machine learning, deep learning, causal analysis, and explainable models. However, common challenges include scalability issues, high computational complexity, dependence on quality datasets, and the need for better interpretability and real-time adaptive learning systems.

***b.* Research Gap**

Despite significant advancements in AI-driven student performance prediction, several research gaps remain. Most existing studies rely heavily on static academic and demographic features, limiting their ability to capture dynamic learning behaviors and real-time student interactions. Current models often prioritize prediction accuracy over interpretability, creating challenges for educators in understanding and trusting AI-based decisions. Additionally, limited integration of peer learning analytics and collaborative interaction data restricts comprehensive modeling of social learning processes. Many proposed approaches also lack cross-institutional validation, reducing model generalizability across diverse educational contexts. Therefore, there is a need for hybrid frameworks that integrate deep learning, explainable AI, and interaction-based analytics to develop accurate, interpretable, and scalable student performance prediction systems.

***c.* Research Trend Analysis of Student Performance Prediction Approaches**

To better understand the evolution of research directions in student performance prediction, a quantitative analysis of recent studies published between 2022 and 2026 was conducted. The reviewed literature was categorized based on dominant methodological approaches including Educational Data Mining, Machine Learning models, Deep Learning techniques, Explainable Artificial Intelligence, Peer Learning Analytics, and AI-driven feedback systems.

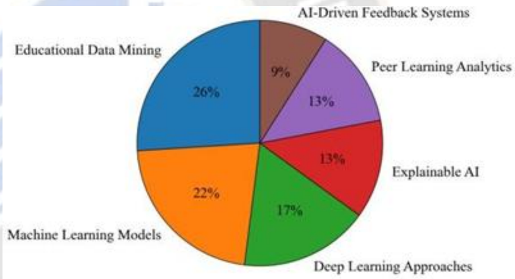

Figure 1 presents the distribution of research contributions across major methodological domains in student performance prediction. Educational Data Mining dominates with 26%, followed by Machine Learning (22%) and Deep Learning (17%), reflecting strong reliance on data-driven predictive approaches. Explainable AI and Peer Learning Analytics each contribute 13%, emphasizing the growing focus on interpretability and collaborative learning analysis. Overall, the trend indicates a shift toward integrated, learner-centered systems that combine prediction accuracy, transparency, and personalized feedback for improved educational decision-making.

III. OVERVIEW OF EDUCATIONAL DATA MINING AND STUDENT PERFORMANCE PREDICTION

Educational Data Mining (EDM) is concerned with deriving significant patterns out of educational data to enhance learning, institutional decision-making, and student success. As digital learning environment continues to grow, a plethora of learner data including academic history and logs of student online interactions are accessible to analysis. One of the most significant uses of EDM has become student performance prediction, allowing identifying students at risk early and aid in data-driven educational interventions.

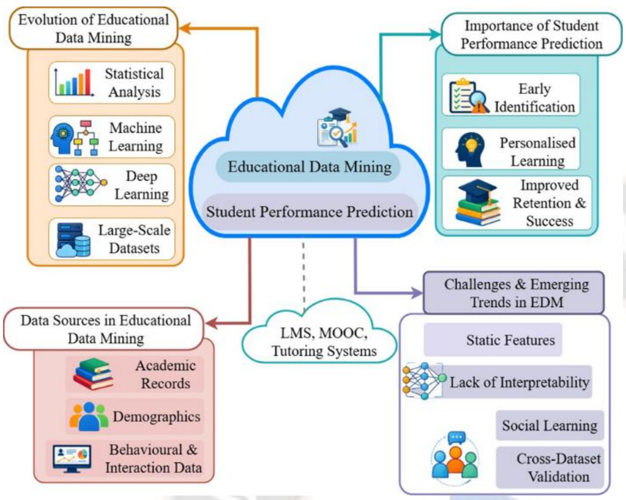

Figure 2: Educational Data Mining Framework for Student Performance Prediction

This figure 2 shows the way Educational Data Mining combines data sources (academic, demographic, and behavioral) with the dynamic analytical methods (statistical, machine learning, and deep learning) to forecast student performance. It also outlines the main advantages of early identification and personalized learning and shortcomings such as non-interpretability, and the necessity of improved social learning integration and cross-data validation.

a. Evolution of Educational Data Mining

Educational Data Mining has developed not only to the old statistical analysis but to the new machine learning and artificial intelligence methods. Initially, simple descriptive statistics and regression models were used to analyse student performance. The classification algorithms, data mining methods, and more recently deep learning models have been introduced to the field over the years. Such development has been motivated by the growing supply of massive scale educational data by Learning Management Systems (LMS), Massive Open Online Courses (MOOCs), and smart tutoring systems. The current EDM is not only concerned with the accuracy of prediction but with the study of the behaviour of the learners, the patterns of engagement, and the process of learning. Importance of Student Performance Prediction

Anticipation of student achievement is a very important aspect of contemporary education. Early warning enables institutions to know the students at risk of failing or dropping out and to offer them academic support in time. This both proactive and reactive action will aid in sustaining retention rates, student success, and better resource distribution. In addition to institutional advantages, performance prediction also underpins personalised learning, through adaptive systems that make use of individual student needs to customise content and interventions. With education becoming more and more data-driven, and with data-driven decisions becoming the norm in this field, predictive models are becoming a crucial tool to both teachers and administrators.

b. Data Sources in Educational Data Mining

Many different sources of data are used in EDM to model and predict student performance. These involve academic data like grades and assessment scores, demographic data and behavioural data gathered on the LMS platforms. Student engagement can be observed based on behavioural data, such as logs of clicking streams, time spent on learning materials, as well as patterns

of submitting assignments. Also, discussion boards and group platforms produce interaction data that are indicative of peer communication and learning processes. A combination of various data sources enables a better comprehension of student learning behaviour.

c. Challenges and Emerging Trends in EDM

In spite of considerable advances, Educational Data Mining is challenged by various issues. The dependence on static and structured data is one of the most significant challenges as it might not be able to capture the complexity of student learning behaviour. The other issue is that model interpretability is not available, especially in high sophistication machine learning and deep learning methodologies which tend to be black boxes. The new developments in EDM focus on overcoming these shortcomings by adding more sophisticated and meaningful data, including social interactions and collaborative learning behaviours. There is also the increasing focus on explainable artificial intelligence so that predictive models can be understandable and meaningful. And, last but not least, cross-institutional and large-scale validation is gaining importance to guarantee the generalisability of predictive models to different educational setting.

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IV. Role of Machine Learning Models in Student Performance Prediction

Machine learning models play a crucial role in predicting student performance by analyzing large volumes of academic, behavioral, and interaction data to identify meaningful patterns. Classification algorithms such as Decision Tree, Random Forest, and Support Vector Machine (SVM) are widely used to categorize students into groups like high-performing, average, or at-risk. These models rely on feature-based prediction, where input variables such as grades, attendance, and peer interaction data from LMS platforms are used to improve prediction accuracy. By incorporating interaction-based features, machine learning models can better capture student engagement and collaborative behavior. The models are trained using historical datasets and evaluated using performance metrics like accuracy, precision, recall, and F1-score to ensure reliability. Overall, machine learning enhances early prediction and supports timely academic interventions.

a. Role of Deep Learning Approaches in Student Performance Prediction

Deep learning approaches play a significant role in improving student performance prediction by capturing complex and non-linear relationships within educational data. Neural networks are particularly effective in processing interaction data from Learning Management Systems, such as student activity logs, discussion participation, and engagement patterns. Sequential models like Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are widely used to track student behavior over time, enabling the analysis of learning progress and temporal patterns. These models can identify changes in engagement, detect early signs of academic risk, and support continuous monitoring. Compared to traditional machine learning methods, deep learning offers advantages such as automatic feature extraction, better handling of large and high-dimensional data, and improved prediction accuracy. However, they require substantial data and computational resources and often lack interpretability, making integration with explainable techniques important.

b. Peer Learning and Interaction-Based Analytics

Peer learning and interaction-based analytics emphasize the role of social collaboration in improving student performance prediction. Unlike traditional models that focus only on individual data, this approach analyzes interactions such as discussions, group work, and peer feedback to better understand learning behavior. Peer learning theory highlights that students learn more effectively through teaching others, collaboration, and shared understanding. Interaction patterns, including participation, responsiveness, and communication structure, provide deeper insights into student engagement and academic success. Collaborative learning environments further support knowledge construction through teamwork and digital platforms like LMS. However, current predictive models still struggle to fully capture the complexity of peer interactions, often relying on simplified participation metrics instead of rich social dynamics.

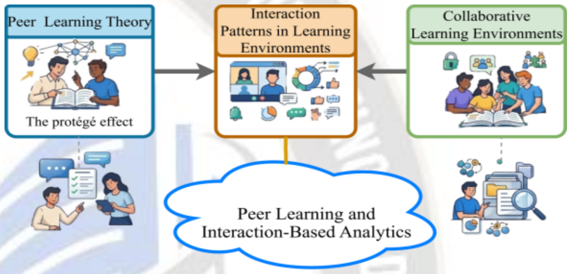

Figure 3: Peer Learning and Interaction-Based Analytics Framework

Figure 3 shows that the peer learning theory, interaction patterns, and collaborative learning environments are all important in comprehending student engagement and performance. It emphasizes the combination of social learning actions and analytics to facilitate predictive modelling and optimize learning results.

c. AI-Driven Feedback and Learning Support Systems

AI-driven feedback and learning support systems extend beyond prediction by providing personalized and timely academic assistance to students. These systems analyze student data and convert predictive outcomes into actionable feedback to improve learning performance. Automated feedback systems deliver instant responses on assignments, quizzes, and activities, helping students identify and correct mistakes quickly. Student support systems use AI to recommend learning resources, schedule tutoring, and alert teachers about at-risk learners. Self-regulated learning tools enable students to monitor their progress, set goals, and improve study strategies using AI dashboards.

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Technologies such as natural language processing, chatbots, and intelligent tutoring systems enhance interaction and guidance. These systems promote continuous learning by offering adaptive and personalized learning paths based on individual performance. They also support educators in making data-driven academic decisions and interventions. Overall, AI-driven learning support systems improve engagement, learning efficiency, and academic success.

Figure 4: AI-Driven Feedback and Learning Support Systems

Figure 4 demonstrates that AI can be applied to bring automated feedback systems, student support systems, and learning systems that are self-regulated into one system. It also focuses on such features as natural language processing to provide feedback, predictive analytics, tutoring system, and chatbots to enhance personalized learning experiences. This integration assists the learners to continue with their studies with constant feedback and tracking of progress and individualized recommendations, which support more efficient and reactive learning.

V. Discussion

The discussion highlights that recent research in student performance prediction has significantly evolved from traditional statistical analysis toward advanced Educational Data Mining, Machine Learning, Deep Learning, and Explainable AI approaches. Existing studies demonstrate strong prediction accuracy and effective early identification of at-risk students using academic, behavioral, and interaction-based datasets. However, many models still face challenges related to interpretability, scalability, and dependence on high-quality institutional data. The growing integration of peer learning analytics and AI-driven feedback systems shows a shift toward learner-centered and collaborative educational environments. Furthermore, explainable and causal learning approaches improve transparency and support data-driven academic decision-making. Overall, future research should focus on hybrid, interpretable, and cross-institutional frameworks that combine predictive accuracy with personalized learning support and real-time educational analytics.

VI. Conclusion

This survey reviewed recent advancements in student performance prediction using Educational Data Mining, Machine Learning, Deep Learning, Learning Analytics, and Explainable Artificial Intelligence techniques. The analysis shows that modern predictive systems significantly improve early risk detection, learner engagement, and data-driven educational decision-making. Despite these achievements, challenges remain in model interpretability, scalability, real-time analytics integration, and cross-institution generalization. The emerging trend emphasizes hybrid frameworks that combine predictive accuracy with explainability and personalized feedback mechanisms. Future work should focus on integrating multi-source educational data, peer interaction analytics, and causal learning approaches to better capture complex learning behaviors. Additionally, developing ethical, transparent, and adaptive AI-based educational systems will be essential for creating intelligent and sustainable learning environments.

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