Economic Sciences
https://economic-sciences.com
ES(2026) 22, (2), 334-341 | ISSN:1505-4683

Artificial Intelligence Approaches for Evaluating Student Performance: A Review of Methods and Trends

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Abstract: *In academic assessments, artificial intelligence (AI) is currently a revolutionary framework that makes it achievable to evaluate student performance in a variety of academic contexts in an adaptable and structured manner. AI programs have an extraordinary effect on the learning, success and performance of students. With an emphasis on methodology-based, quantifiable outcomes, and usability in actual academic environments, this study provides a comprehensive and thorough analysis of cutting-edge AI approaches such as Machine Learning (ML), Deep Learning (DL) and Natural Language Processing (NLP) published from 2022 to 2026. Additionally, this study evaluates emerging trends like integrated analysis, explainable AI (XAI) and fairness-based models. The primary conclusion of this paper shows that, in complicated circumstances, DL methodologies regularly dominate classical ML techniques in terms of accurate prediction. Moreover, the absence of uniform assessment models, inadequate incorporation of theoretical concepts in education and restricted potential for generalization among databases are among the primary difficulties addressed. This work influences it because it offers a cohesive and thoroughly reviewed benchmark that helps professionals as well as scholars to create accurate, comprehensible and morally sound AI platforms or models. Furthermore, this comprehensive review makes it easier to implement AI evaluation instruments in actual academic institutions.*

Keywords: *Artificial Intelligence, Machine Learning, Deep Learning, Student Performance, Prediction Model, Education technology, AI in Education.*

I. INTRODUCTION

Platforms for learning online are growing in popularity by virtue of their adaptability and capacity to connect with more individuals [1-3]. Reduced expenses, convenient scheduling, better detailed knowledge including guided activities and educational environment customization are the primary benefits of this educational framework for students [4]. Considering such advantages, instructors nevertheless discover it extremely difficult to keep an eye on their students. The enormous number of students in any given course and not having in-person connection make it extremely difficult to continue keeping records of every student when compared with conventional learning environment [5]. A crucial component of contemporary learning is assessing student performance, which has a significant impact on learning strategy, individualized instructions and decisions made by institutions [6]. Subjectiveness, restricted flexibility, incomplete responses and challenges in identifying periodic trends in learning are some of the major drawbacks of classical assessment techniques consisting of manually performed scoring, regular examinations and teacher analysis [7-9]. These limitations make it more difficult to determine student performance and to offer tailored solutions.

AI is rapidly emerging as a game-changing instrument in learning, especially when it involves analyzing data about students to advance instructions and student performance [10]. Instructors can gain prospective on how students perform, participate and learn by using AI tools to analyze vast amount of student information with greater efficiency. These findings can be utilized to determine students who require extra assistance and to guide individualized training [11]. AI is a crucial tool for education because of its ability to analyze complicated data sets, forecast student performance and recommend solutions [12-13]. The automatic analysis of unorganized material, such as academic papers, forum discussions and responses are made possible by NLP techniques which offer observations about understanding, reasoning and drafting abilities of a student [14]. Similarly, to reliably anticipate results of students and facilitate immediate support, ML systems can handle organized academic data, which includes scores, enrollment and coursework [15]. Furthermore, DL methods assist in simulating linear methods of learning as well as reveal difficult trends in student learning pathways [16]. Teachers can address the drawbacks of conventional assessment approaches by utilizing AI to provide standardized, rapid and detailed performance evaluations. The use of predictive analytics powered by AI enables educational organizations to estimate student achievement, customize teaching routes and establish early detection strategies in operations, providing useful information for curricular preparation and student assistance [17].

This work highlights the most popular approaches, important results, comparative performance, advantages, disadvantages and present research trends, which methodically summarizes AI strategies utilized to assess student performance. This work is novel as it is integrating well-organized analysis to research questions to lead the evaluation, quantitative comparative analysis and unbiased review assessment into a unified platform. Although the outcome of this study assists academics as well as professionals to determine the most successful AI systems and guide upcoming academic analytic initiatives. The major contributions of this work are:

- Offers a thorough overview of ML, DL and NLP approaches for evaluating student performance using statistical performance values
- Present comprehensive review of academic papers published from 2022 to 2026 mainly focused on examining student performance using AI approaches.
- Identifies the best performing methodologies for assessing student performance by presenting an organized comparison of achieved accuracies in table form.
- Highlights the emerging trends, limitations and research directions.

II. REVIEW METHODOLOGY

A. Search Strategy

Major academic databases such as ScienceDirect, SpringerLink, Web of Science, Scopus, IEEE and Google Scholar were used to find appropriate research work. A variety of keywords were used in this investigation including "ML in education", "automated student performance evaluation using NLP", "AI in evaluating student performance", "DL in student assessment", "AI in education system", "Student performance predicting using AI", etc. To investigate novel advances in AI approaches, the search was restricted to articles published from 2022 to 2026. Moreover, the findings of this research were refined by using "AND" and "OR" Boolean operators.

B. Inclusion and Exclusion criteria

The inclusion requirements outlined below were used to guarantee reliability as well as appropriateness:

- Research articles concentrating on AI methods for assessing or anticipating student performance
- Conference papers and peer reviewed journal articles
- Published from 2022 to 2026
- Research papers incorporating quantitative assessment by utilizing standard parameters such as accuracy.

Exclusion requirements are given below:

- Research articles irrelevant to student performance assessment
- Preprints, blogs and documents
- Scholarly articles published prior to 2022
- Publications with inadequate methodology specifications and without quantitative assessment

C. Process of Study Selection

127 papers were found in the first search; these were filtered by evaluating their abstract and title. After eliminating non-relevant scholarly articles, the rest of the 75 publications underwent a comprehensive evaluation. Publications that satisfied the requirements for inclusion were chosen for in-depth examination. Only 29 excellent as well as pertinent articles were incorporated in this student in response to the above thorough screening process.

D. Collection & Evaluation of Data

Important details, such as the AI method employed, the utilized data set, the assessment criteria and the estimated results, were taken from every single chosen article. To find trends, patterns and comparison observations between various methodologies, the retrieved data were further analyzed.

E. Research Questions

The evaluation is directed by well-defined research questions (RQs) to reinforce the evaluation's framework and bring it into compliance with organized study methods. Quantitative results, comparison conclusions and a summary of collection of current publications are used to answer every RQ.

- RQ1: Which AI methods are typically applied to the assessment of student performance?
- RQ2: Which AI techniques – ML, DL or NLP – performs most effectively in evaluating student performance?
- RQ3: What are the emerging trends, primary barriers and unsolved research needs in the current standard scholarly investigations?

III. METHODS, QUANTITATIVE EVALUATION & COMAPRISON ANALYSIS

This section examines AI-driven approaches for evaluating student performance, mainly ML, DL and NLP algorithms. Additionally, every RQ is answered in this section by combining empirical results, comparison analysis and ana examination of published work. Table I provides a quantitative evaluation and comparison analysis of existing selected studies based on their objective, methods, datasets, data types and obtained results.

In literature, ML systems are thoroughly investigated to evaluate student's performance as these models can effectively assess organized academic data and produce meaningful prediction results. Sarwat et al. (2022) [18] presented an approach using a deep-layer driven support vector machine in conjunction with an enhanced conditional generative adversarial network for predicting how well students perform during in-class and at-home tuition with an accuracy of 98.2%. To classify students' performance in academia in virtual and distant learning programs using ML method, Gámez-Granados et al. (2023) [19] suggested a fuzzy ordinal classification technique called FlexNSLVOrd, which achieved 85.5% classification accuracy. In study Chen et al. (2024) [20], the Random forest algorithm was used to evaluate learning behavior produced by different educational environments to forecast ultimate performance of students with accuracy 98.15 percent and offer a framework for making decisions about lowering dropout risk of students. Moreover, with an excellent accuracy of 95 percent, Adebanjo et al. (2025) [21] employed the Logistic Regression approach to detect students who have a high risk of dropping out and provide them with appropriate assistance to improve educational assistance. Guo et al. (2025) [22] proposed a two phase XGBoost inspired classification system intended to accurately detect student academic difficulties by means of methodical predictive modeling to assist higher education institutions in rapidly recognizing educational risks, implementing specific strategies and improving the effectiveness as well as accuracy of educational early detection. The results of this study demonstrated that the calculated accuracies for initial and 2nd phase of this approach were 90.7 and 71.5 percent, respectively.

Similarly, the most advanced methods for assessing student performance are DL systems, which use layered neural structures to describe intricate, irregular and dynamic trends in learning using academic data. Li et al. (2022) [23] presented an integrated deep neural network-based algorithm that predicts educational performance with 94 percent accuracy by autonomously extracting attributes from diverse and inconsistent behavior data of students. Shen (2024) [24] showed that the enhanced CNN-LSTM framework has major benefits for both facilitating adaptive learning process modification and anticipating the academic achievement of students with 97.64 percent of accuracy. Kalita et al. (2025) [25] utilized Bi-LSTM network to classify low-performing students in advance and estimate their grading point average so that teachers and corresponding regulators can intervene promptly. The experimental findings of this study demonstrated that the model outperformed with an overall accuracy of 88.23 percent. Furthermore, Lin et al. (2026) [26] created and assessed a multi-disciplinary knowledge tracing (KT) structure that is capable of accurately predicting student performance in Massive Open

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ES(2026) 22, (2), 334-341 | ISSN:1505-4683

Online Courses (MOOCs) by utilizing previous academic experience of students throughout various lessons with approximately 88 to 91 percent accuracy.

Recent research on evaluating student performance has focused more on NLP techniques, especially when it comes to examining unorganized text data and deriving significant findings about understanding, participation and analytical skills. Chandrapati & Rao (2024) [27] proposed a new hybrid system called Descriptive Answer Evaluation System (DAES) by integrating BERT and transformer-based DL, which has a 95 percent accuracy and represents a major development in education evaluation approach used in automatically assessing descriptive responses provided by students and then evaluates student performance. moreover, the research presented by Wang (2024) [28] has the primary goal to make highly accurate prediction about students' performance using DistilBERT with LSTM and Spotted Hyema Optimizer (SHO) to identify deeper underlying patterns in collected data set and this study demonstrated 98.7 percent accuracy. Venkatachalam & Sivanraju (2023) [29] combined NLP and DL approaches to estimate student achievements. MLP, CNN and LSTM architectures are integrated LDA driven NLP subject modeling for 91.7% accurate extraction of mental health attributes.

TABLE I. COMPARATIVE ANALYSIS

Reference	Objective	Methods	Dataset	Data type	Results
Sarwat et al. (2022) [18]	To predict how well students perform during in-class and at home tuition	SVM + CGAN	OULAD	Structured and temporal data	Accuracy: 98.2%
Gámez-Granados et al. (2023) [18]	To classify students' performance in virtual and distant learning using ML method	Fuzzy Ordinal	OULAD	Structured tabular data	Accuracy: 85.5%
Chen et al. (2024) [19]	To evaluate learning behavior data and forecast student performance in different educational environment	Random Forest	UCI	Structured tabular data	Accuracy: 98.15%
Adebanjo et al. (2025) [20]	To detect students who have a high risk of failing and to improve their educational assistance	Logistic Regression	UCI	Structured tabular data	Accuracy: 95%
Guo et al. (2025) [22]	To detect student academic difficulties and assist higher educational institutions in early detection of risks and implement specific strategies	XGBoost	OULAD	Structured and behavioral data	Accuracy of 1st phase: 90.7% Accuracy of 2nd phase: 71.5%
Li et al. (2022) [23]	To predict educational performance by autonomously extracting attributes from student behavior data using DL methods	DNN	Regular behavior data from Beijing University students	Behavioral time-series + structured	Accuracy: 94%
Shen (2024) [24]	To facilitate adaptive learning process modification and anticipate	CNN + LSTM	Exclusive organizational data set from the	Textual + Behavioral + structured	Accuracy: 97.64%

	student performance using DL methods		educational management system of a big public school		
Kalita et al. (2025) [25]	to classify low-performing students in advance and estimate their grading point average	Bi-LSTM	UCI	Structural and tabular	Accuracy: 88.23%
Lin et al. (2026) [26]	To create a multi-disciplinary KT structure which predicts student performance in MOOCs using previous academic experience of student	Deep knowledge tracing	Course-specific KT data using MOOCs	Behavioral time-series + Sequential	Accuracy: 88 to 91%
Chandrapati & Rao (2024) [27]	To develop a hybrid system using NLP and DL models for evaluating descriptive responses of students	BERT and transformer-based DL	Institutional student performance dataset	Behavioral and structured	Accuracy: 95%
Wang (2024) [28]	To make highly accurate predictions about students' performance using AI methods	DistilBERT with LSTM and SHO	OULAD	Structured and behavioral	Accuracy: 98.7%
Venkatachalam & Sivanraju (2023) [29]	To integrate NLP and DL approaches for estimating student achievement	MLP, CNN and LSTM architectures + LDA	Nonpublic dataset	Textual + demographic + Structural	Accuracy: 91.7`%

A. *Response to RQ1*

From literature, it can be analyzed that the most popular approaches for assessing student performance are ML methods considering their ease of application, comprehension and efficiency with organized data. Table I shows the prominent ML methods such as SVM, Fuzzy, Random Forest, Logistic regression and XGBoost. Meanwhile, latest research indicates an increasing trend favoring DL techniques that are more appropriate for simulating continuous and linear learning patterns which include DNN, CNN, deep knowledge tracing and bi-LSTM. Simultaneously, textual and unorganized data are being analyzed by NLP and assist in evaluating student performance such as BERT. In general, the development shows a shift beyond standard ML and to blended NLP and DL driven systems for more detailed as well as context-sensitive assessments of student performance.

B. *Response to RQ2*

The reviewed research shows that DL methods are the most successful in all aspects, in terms of dealing with multimodal, sequential and behavioral data from schools. This is particularly evident for hybrid DL methods like DNN driven algorithms (94%), DistilBERT with LSTM and SHO (98.7%) and CNN + LSTM (97.64%). On organized data sets, classic ML algorithms like logistic regression (95%), SVM (98.2%) and Randon forest (98.15%) also obtain excellent accuracy, demonstrating that ML is still extremely fierce in clearly specified tabulated situations. In the meantime, high accuracy up to 95 percent is attained by both standard and mixed DL-NLP models such as BERT and transformer-based DL. In complicated and interdisciplinary learning context, DL driven mixed approaches often perform somewhat better than NLP and ML.

C. Response to RQ3

Mixed transformer-powered and DL methods like BERT, DistilBERT-LSTM and CNN-LSTM methods are clearly on the rise in recent studies. These algorithms surpass classic ML techniques by managing heterogeneous, text-based and linear data from educational institutions. For more thorough performance anticipation, multimodal and behavioral data sets that combine educational data and written answers are also becoming progressively popular. Restricted system interpretability, poor domain specific classification, the absence of assessment procedures and defined data sets, particularly NLP and DL algorithms developed using organizational or OULAD dataset, remain significant challenges. Moreover, the concerns about data confidentiality and class disparity limit system performance even more. To make more reliable decisions regarding education, subsequent studies must concentrate on creating scalable, equitable and explainable AI models in addition to evaluating multidimensional databases and the incorporation of logical inference methodologies.

IV. TRENDS, ISSUES AND FUTURE ANALYSIS STRATEGIES

There has been a noticeable shift from independent forecasting techniques to combined and adaptive analytical learning systems in the latest advances in AI-powered evaluation of student achievement. Integrated analysis is a significant new trend that combines organized educational documents, unorganized texts and logs to improve context knowledge and forecasting precision. The algorithms used in DL can be made more transparent by using XAI approaches like SHAP. Teachers can comprehend attribute submissions, evaluate expected outcomes and develop confidence in autonomous evaluation tools with the help of XAI. Simultaneously, fairness-aware algorithms are receiving greater consideration to reduce discrimination associated with educational distinctions and guarantee impartial assessment.

Considering such improvements, there are still significant scientific and real-world problems. Reproducibility is restricted by different attribute interpretations and a shortage of standardized evaluation databases at the data level. Transformer-driven and DL methods have tremendous complexity in computation and poor interpretability which limits their use in actual academic context at the model level. Most systems are developed and verified in regulated conditions at the implementation level, which leads to poor multi-institutional adaptation. Safeguarding confidentiality, bias reduction and fairness are examples of ethical issues that are still not properly resolved.

Further studies should concentrate on creating cohesive multidimensional systems that guarantee applicability throughout academic setting. Post-hoc explanations ought to lead the way to intrinsically interpretable structures in XAI. Adaptable implementation must also be supported by the integration of privacy-protecting methods and federated learning. Lastly, to guarantee that predictive algorithms result in real-world initiatives instead of just numerical results.

V. DISCUSSION

The review of the existing published work shows that while AI methods have made major advances in evaluating student performance, their practical application is still limited. Finding a balance between understandability and forecasting accuracy is a major problem. Methods for DL are extremely successful in relation to ability to predict since they continuously show outstanding results over behavioral and time-series data sets, especially deep knowledge tracing and LSTM-driven systems. But due to their opaque character, instructors are less confident in them.

Despite having somewhat lower detection accuracy, standard ML systems are still very helpful because of their applicability for organized data, efficient computation and clarity. In practical situations where clear explanation is crucial, such frameworks are frequently chosen. Although, they achieve clear connection with human assessment, NLP-driven techniques have become predominant methods for analyzing unorganized data, however they are limited by subject awareness and data needs.

Moreover, the disparity in assessment methods among publications is a further significant finding. Variations in measurement parameters, features and databases make comparative analysis difficult and less the overall value of study results. This emphasizes the necessity of uniform assessment processes and criteria.

Due to the dependency on secondary literature, which limits clear comparison among research due to inconsistent provided data sources, assessment measures and research settings, the present review is constrained. The inclusion of serval databases in numerous evaluated papers restricts uniformity and can result in bias in choice. Lastly, although data methods vary, the analysis mostly concentrates on evaluation accuracy and excludes a meta-analysis based mathematical evaluation.

VI. CONCLUSION

This review paper analyzes different AI approaches used for evaluating student performance published from 2022 to 2026. It is observed that by facilitating standardized, flexible and adaptable examination platforms, AI methods have revolutionized the evaluation of student performance. Although NLP and DL techniques improve accuracy in complicated as well as unorganized data contexts, ML systems provide effectiveness and interpretability. Nonetheless, ethical concerns, issues with generalization and interpretability still exist. To increase dependability and acceptance, future investments need to concentrate on creating explainable methods, uniform evaluation guidelines and integrated systems. By overcoming such concerns, AI's influence in educational settings is going to be strengthened and its compatibility with educational objectives will be guaranteed.

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