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A Comprehensive Survey Of Artificial Intelligence Techniques For Intelligent Student Learning Analytics And Privacy-Aware Decision Support

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Abstract— The exponential development of digital learning platforms has resulted in large volumes of education-related data such as educational records, learning behaviors, cognitive tests, and engagement. The field of Intelligent Student Learning Analytics has become a promising analyze topic as it uses artificial intelligence methods to investigate these heterogeneous data for predicting academic performance, analyzing learner behavior, detecting learner engagement, identifying risks and providing personalized learning. In this survey, review of twenty recently developed methods, which have been reported from 2024 to 2026, related to machine learning, deep learning, explainable artificial intelligence (XAI), federated learning and privacy-preserving learning analytics. A variety of techniques have been utilized in these surveyed methods to enhance educational decision-making and personalized learning; these include but not limited to support vector classification, random forest, artificial neural networks, convolutional neural network, bidirectional long short-term memory, gated recurrent unit, HybridStackNet, SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), differential privacy and federated learning. The survey comprehensively reviews existing techniques, datasets, applications, strengths, weaknesses, etc., emphasizing existing challenges such as lack of generalization of models, heterogeneous nature of educational data, lack of multimodal data integration, privacy issues and lack of interpretable/trustworthy learning analytics. Moreover, the survey discusses existing work of scalable, multimodal and privacy-preserved intelligent learning analytics system that can support reliable educational decision-making.

Keywords—Artificial Intelligence, Deep Learning, Explainable Artificial Intelligence, Federated Learning, Machine Learning, Student Learning Analytics.

I. INTRODUCTION

This rapid growth has resulted in huge amounts of data being produced by these online educational platforms. Such intelligent student learning analytics attempts to use machine learning and deep learning to discover learning representations and make predictions about academic performance, detect struggling students and provide personal educational assistance.

Current student analyses have proved that computational approaches can be very efficient in various types of education data. Multimodal educational data mining systems have been developed in the context of academic courses' recommendations and students' performance predictions through combining different learning features [1]. Intelligent testing approaches have analyzed cognitive features and e-learning interactions in order to facilitate automatic student assessment and learning monitoring [2]. Machine learning-based engagement detection methods have used behavioral learning patterns to identify student engagement [3]. The deep learning models that integrate behavioral and emotional characteristics have provided even better engagement analysis through the discovery of intricate patterns from the students activity data [4]. There have been some recent investigations regarding advanced deep learning architectures in analyzing the learners' behavior and academic predictions as well. Some deep neural models have been developed for the analysis of the students' engagement activities and dynamic learning behaviors [5]. The temporal learning architectures like attention-based GRU models have enhanced the learner behavior prediction process [6]. Approaches for explainable deep learning

have been proposed to increase transparency through detection of significant features that affect student performance predictions [7]. Neural network-based early prediction methods have been developed to proactively identify students who at risk of poor academic performance [8]. Predictive models based on Bi-LSTM with SHAP have increased explainability in academic performance prediction [9]. Hybrid deep learning models have additionally improved academic achievement and engagement prediction through the incorporation of various learning representations and explainability-based analysis methods [10].
Despite all that, the current methods have some drawbacks, such as lack of generalization capability for various educational settings, reliance on certain data sets, inadequate consideration of the multimodal learning data and difficulties with privacy issues and model explainability. Therefore, an adaptive, explainable and privacy-preserving intelligent learning analytics is required.

II. Background Study

B. Tang et al. (2024) [11] proposed an innovative deep ensemble learning method for predicting student achievement through education-related characteristics. Deep ensemble learning used several models to achieve better accuracy and stability of prediction. But the lack of diversity in features hindered generalization capability. The researchers succeeded in enhancing the prediction accuracy.
F. S. Alrayes et al. (2025) [12] presented a method of privacy-preserving statistical learning for high-dimensional data domains. This method combined learning based on optimization with privacy preservation schemes. However, it mostly emphasized data security rather than personalized learning in education. It was noted that the scheme ensured good predictive accuracy.
W. Ahmed et al. (2025) [13] proposed a model of explainable machine learning that can predict academic performance. The approach used interpretable machine learning to determine critical variables within the education sector. Nonetheless, there was a lack on dynamic learning behavior. The model made decision making easier through performance prediction.
H. Mastour et al. (2025) [14] developed explainable artificial intelligence for the purpose of forecasting medical students' performance. For the purposes of this analyze, ensemble learning models along with interpretability analysis were used. However, the model used was domain-specific and not applicable in other fields of education.
S. Gunasekara and M. Saarela (2025) [15] investigated explainable AI methodologies for application to education. It considered the role of interpretation approaches in increasing the trust in AI-assisted learning platforms. Nonetheless, the problems connected to the quality of explanations and implementation of such approaches was not solved.

TABLE I. COMPARATIVE ANALYSIS OF PRIVACY-PRESERVING AND PERSONALIZED STUDENT LEARNING ANALYTICS APPROACHES

Author, Year and Ref. No.	Concept	Method Used	Limitations	Results in Values
Y. Zhao et al. (2025) [16]	Privacy-preserving grade prediction	DP-TabNet with feature interpretation	Privacy can reduce prediction efficiency	Accuracy: 80%
Y.H. Lai et al. (2024) [17]	Personalized federated learning for student prediction	Adaptive feature extraction and category prediction	Challenging under non-IID data	Accuracy: 94% after 20 rounds
Y. Jiang et al. (2024) [18]	Privacy-aware personalized learning	Knowledge distillation-based federated learning with differential privacy	Privacy–accuracy trade-off issues	Accuracy: 76.5% with reduced communication rounds
R. Gutiérrez et al. (2025) [19]	Secure emotion detection in education	Federated learning-based emotion recognition	Limited large-scale deployment capability	Precision: 87%, Recall: 85%, F1-score: 86%
S. Chen and X. Qi (2025) [20]	Privacy-preserving student performance prediction	Entropy-adaptive differential privacy federated learning	Requires optimal privacy parameter selection	Accuracy: 92.7%, Macro-score: 92.1%

Table I represents a comparison of privacy-preserving learning analytics strategies that incorporate federated learning, differential privacy and explainable machine learning models. These strategies improve personalized learning prediction while solving issues concerning data privacy, heterogeneous education setting and trustworthy decision-making based on AI.

A. Research Gap

The current techniques in student learning analytics consider performance prediction, engagement analysis, or privacy-preserving techniques in isolation. Existing researches primarily focus on performance prediction, engagement analysis, explainable AI, or privacy preservation independently. Limited analysis has integrated multimodal learning analytics, explainable AI and federated privacy-preserving learning into a unified intelligent. Hence, a robust intelligent learning analytics method is needed for enabling effective monitoring of students and educational decisions based on personalized learning analytics.

III. Intelligent Student Learning Analytics

According to the survey of Intelligent Student Learning Analytics, the application of Artificial Intelligence is used for analyzing different kinds of education data including learning behavior, student performance, cognition pattern and engagement. Such an analysis assists in developing a precise model of the students and detecting risks, which can be addressed with proper recommendations. This method combines predictive analytics, explainable AI and privacy preserving methods to enable intelligent decision making in education.

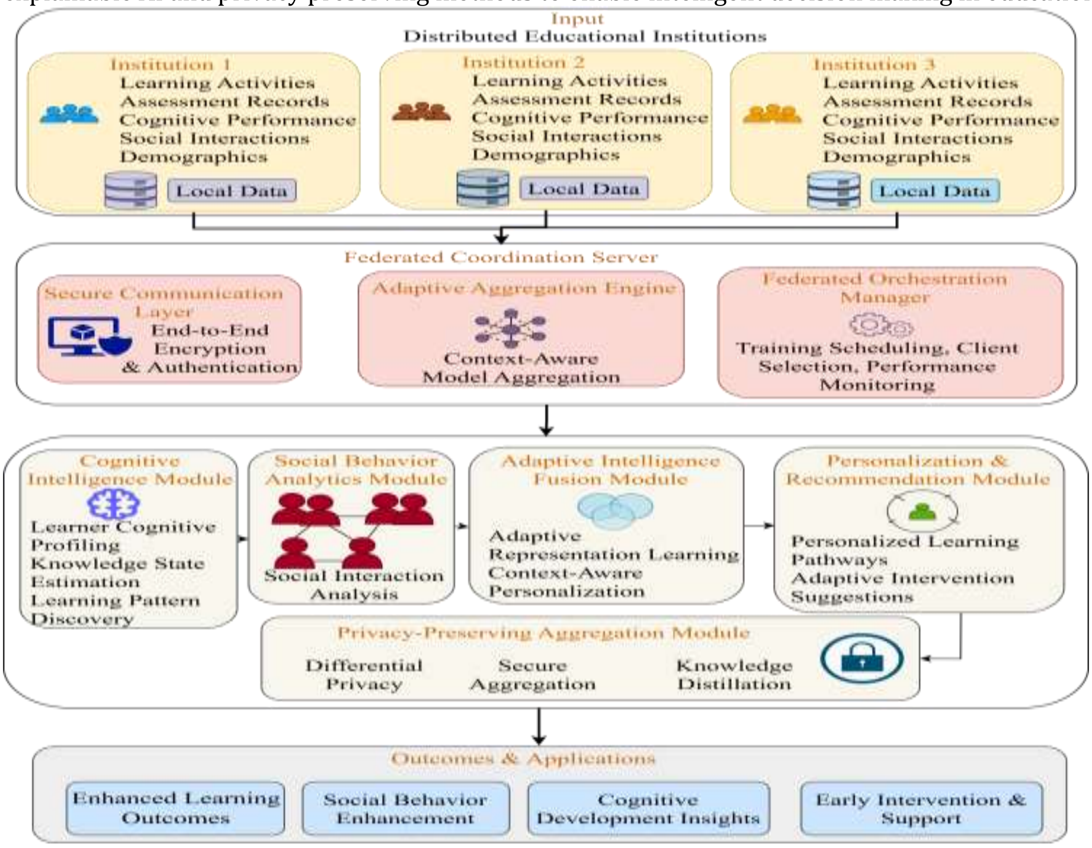

Fig. 1. Adaptive Federated Intelligence for Cognitive and Social Learning

Fig. 1 illustrates an adaptive federated intelligence architecture that combines cognitive analytics, social behavior analysis and privacy-preserving learning across educational institutions. It supports personalized learning, cognitive development, social engagement and timely intervention through secure collaboration.

A. Multimodal Student Behavior Representation and Learning Analytics

Learning representation models using multimodality learning capture the learning situations of students through the extraction of patterns from its learning records, activities, cognitive processes and interactions [1]. This modeling strategy looks at various education aspects to uncover the underlying associations between learning elements, making it possible for profiling and predicting the performance of learners.

The cognitive and behavioral data-driven representation models include aspects such as learner characteristics, test answers and engagement information in order to establish unique student profiles [2]. These approaches are able to create an all-encompassing representation because it takes into account the abilities and differences in behavior of the individual learners.

The approach of engagement-based representation learning recognizes significant behavioral and emotional cues related to student engagement and participation [3]. Machine learning algorithms use the method of interaction patterns, activities and behaviors of learners to derive meaningful patterns of engagement and increase the knowledge about motivation and performance aspects.

Deep-learning based multimodal representation techniques provide improvements to educational analytics by combining visual, behavioral, emotional and academic features into one single model of the learners [4]. These allow the automatic extraction of higher-level representations of complex educational data sets and contribute to increasing engagement detection, monitoring and personalization accuracy.

B. Deep Learning-Based Student Performance Prediction and Explainable Learning Analytics

Deep learning-based models for predictions are based on understanding complicated educational information through automatic acquisition of higher-level features from information about students' academic history, learning behavior and performance attributes [7]. The nonlinear correlation between many learning variables is identified in such approaches, which makes it possible to predict student performance and detect educational risks in advance. The use of deep neural networks with education-specific knowledge increases the accuracy of predictions.

Performance prediction models in its initial phase aim to detect students who at risk before the end of the process of carrying out academic tasks [8]. Models using neural networks use early learning markers, virtual learning environment behavior and assessment features to predict different performance classes.

Temporal learning models, like Bi-LSTM, are capable of recognizing temporal dependencies in student's learning activities via analyzing the development of academic progress over time [9]. Moreover, temporal learning models have a great capacity for representing the changing nature of the learning process and integrating explainable methods like SHAP to determine influential factors.

The hybrid models of academic analytics based on deep learning include several learning characteristics, making it possible to make accurate predictions regarding the success and engagement of the learners [10]. The use of both sophisticated neural network architecture and interpretable methods makes it possible to predict with accuracy the effect that certain factors like learner engagement and academic performance have.

C. Explainable, Privacy-Preserving and Personalized Learning Intelligence

XAI-based learning models concentrate on enhancing the predictability system's transparency and interpretability through determining the factors that affect the student outcomes [15]. It provides explanations for the choices and predictions that is understandable by humans, hence making it easier to identify the relationship between learning attributes and student success. In this regard, XAI is used to enhance the reliability of AI-enabled education decision-making systems.

Privacy-preserving learning systems are capable of overcoming the problems that arise from processing sensitive learner data through the implementation of privacy measures into the models for predictions [16]. Differential privacy techniques safeguard the learner data while still being able to achieve accurate predictions. This enables educational establishments to perform intelligent analysis without violating the privacy of students.

The use of personalized federated learning allows for the creation of adaptive student models that learn from distributed educational datasets without sending sensitive data to centralized servers [17]. This can improve personalized feature selection and classification by solving the problem of data heterogeneity, thus allowing for personalized and intelligent educational services.

D. Machine Learning Techniques for Intelligent Student Performance Analytics

Machine learning techniques serve as an efficient tool for educational data analysis using patterns obtained from academic and behavioral attributes of the students. Methods for machine learning used to increase the effectiveness of learning analytics by performing predictive analysis, calculating engagement metrics and identifying those elements influencing learner's performance.

TABLE II. COMPARATIVE ANALYSIS OF MACHINE LEARNING-BASED STUDENT LEARNING ANALYTICS APPROACHES

Ref. No.	Method / Model	Dataset	Process	Novelty / Key Contribution	Results
[5]	Explainable ML-Based Performance Prediction	Academic performance dataset	Uses student academic features for prediction and analysis	Provides interpretable predictions by identifying important performance factors	RMSE: 0.1050, MAE: 0.0837, achieved high R^2
[8]	Support Vector Classification (SVC)	Student performance dataset	Uses multimodal educational features for	Combines different learning attributes for academic	Accuracy: 78.04%, F1-score: 75.37%

			classification	prediction	
[9]	Random Forest-Based Cognitive Assessment	E-learning dataset	Analyzes cognitive and assessment features for learner evaluation	Supports intelligent student assessment using learning patterns	Accuracy: 92.16%, Precision: 92.36%
[10]	ANN and Decision Tree Classification	Educational dataset	Classifies student outcomes using ML models	Improves transparency through explainable ML analysis	ANN Accuracy: 92.09%, DT Accuracy: 89%
[12]	Decision Tree-Based Engagement Prediction	Online learning dataset	Analyzes quiz and exam engagement patterns	Detects learner participation using behavioral features	Quiz Accuracy: 97%, Exam Achieved high accuracy
[13]	Explainable ML Performance Model	Academic dataset	Predicts outcomes using feature-based ML analysis	Identifies key factors influencing student performance	RMSE 0.1050, MAE 0.0837 and high R^2

Table II is a comparison of some of the machine learning techniques that have been applied in the field of student learning analysis, performance prediction and engagement evaluation. There are certain techniques that have utilized education data, behavior data and explainable artificial intelligence techniques to build intelligent models that used to provide personalized learning support and predict academic risks.

E. Deep Learning Approaches for Intelligent Educational Analytics

The deep learning techniques applied to student analytics have sophisticated neural network structure that enables to analyze various data including educational data such as academic data, behavioral data and learning processes. Such methodologies facilitate the improved prediction of performance and analysis of engagement through intelligent pattern recognition.

TABLE III. COMPARISON OF DEEP LEARNING-BASED STUDENT ANALYTICS APPROACHES

Ref. No.	Method / Model	Dataset	Process	Key Contribution	Results
[4]	CNN, ResNet50, VGG16, InceptionV3	Student video dataset	Extracts behavioral and emotional engagement features from videos	Uses deep visual learning for engagement detection	CNN achieved 83% testing accuracy; ResNet50 achieved 82% accuracy
[6]	TSA-GRU	ASSISTments dataset	Learns sequential learning behaviors using attention-based GRU	Improves learner behavior prediction with temporal attention	Achieved 95.60% accuracy and 0.0209 loss
[9]	Bi-LSTM + SHAP	Academic performance dataset	Models learning sequences and feature importance	Provides interpretable performance prediction	Achieved 88.23% accuracy with better performance than ML models
[13]	IC-BiSGRU-Net	Multimodal engagement dataset	Analyzes learning activities using	Enables real-time student engagement	Achieved 96.21% accuracy and

			BiGRU networks	monitoring	achieved high F1-score
[14]	ANN + SPPE	Mathematics performance dataset	Integrates domain knowledge with ANN prediction	Improves explainability of student prediction	Improved accuracy by 26.9% over original ANN
[18]	HybridStackNet	Higher education dataset	Combines deep models with LIME and PDP analysis	Provides accurate and explainable prediction	Achieved high accuracy and AUC

Table III provides an analysis of the deep learning analytical techniques used with behavior, academic and multimodal learning data for the prediction of performance and engagement measurement. This table shows the ability of the deep neural network in making precise and personalized decisions in the education field.

IV. Discussion

The examined methodologies prove that intelligent learning analytics have become an integral part of modern educational systems. Machine and deep learning algorithms are effective in making performance predictions, identifying engagement patterns and detecting at-risk students using automated feature learning and prediction techniques. Explainable AI and privacy-preserving approaches also ensure the reliability and validity of educational systems as it used to produce transparent predictions without compromising the security of the learner's data. Nevertheless, there are some difficulties in applying intelligent learning techniques due to data heterogeneity, generalization issues, privacy risks and practical application of educational systems. In future have to be devoted to building adaptive, interpretable and secure intelligent learning analytics.

V. Conclusion

In this survey, an extensive overview of artificial intelligence methods used in intelligent student learning analytics for academic prediction, learning behavior analysis, engagement detection and personalized education has been provided. Twenty references analyzed in terms of using the techniques of machine learning, deep learning, explainable artificial intelligence, federated learning and privacy preservation in education. The literature review has revealed that more sophisticated learning algorithms such as neural networks, temporal deep learning models, ensembles and interpretable AI algorithms have been successfully used for extracting valuable patterns from various types of data associated with academic, behavioral, cognitive and multimodal education. Nevertheless, there are still several problems with data heterogeneity, generalization ability, privacy, multimodal data handling and real-time application. The future development will be oriented towards designing adaptive, scalable and trustworthy systems of learning analytics through the integration of multimodal representation learning, explainable AI and federated intelligence. This type of system can be able to give recommendations in a transparent manner, monitor the learners continuously and facilitate decisions.

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