CSCSTI 14.35.01 https://doi.org/10.47751/skpu.1937.v43i1.2

STUDENT PERFORMANCE PREDICTION IN INTELLIGENT TUTORING SYSTEMS: METHODS, CHALLENGES, AND FUTURE PERSPECTIVES

Razali Yaakob[1], Magagula Alson Khumbulani[2]
[1]Associate Professor, PhD, [2]Masters Student
[1, 2] University of Putra Malaysia. Serdang/Malaysia.

[1]ORCID: 0000-0002-8228-5753, e-mail: razaliy@upm.edu.my
[2]ORCID: 0009-0005-1153-6315, e-mail: alsonmag@gmail.com

Abstract

The application of predictive models within Intelligent Tutoring Systems (ITS) has seen significant advancements, enhancing personalised learning and early identification of at-risk students. However, challenges related to model generalisability, interpretability, data quality, and fairness persist, limiting their widespread adoption across diverse educational environments. This review synthesizes findings from 58 studies published between 2019 and 2024, sourced from databases such as IEEE Xplore, Scopus, Science Direct, Google Scholar and SpringerLink. The literature selection was based on keywords like "student performance prediction" and "AI in education". Techniques, datasets, and evaluation metrics were categorized to identify thematic trends and highlight challenges and opportunities for ITS. The findings indicate that hybrid models (e.g., CNN-LSTM, RLCHI), ensemble learning, and integration of multimodal data significantly enhance predictive performance. Techniques like SHAP and LIME have improved interpretability, while models incorporating socio-demographic and behavioural data provide better insights into student learning patterns. Nonetheless, generalisability and fairness remain key challenges, requiring diverse datasets and fairness-aware modelling approaches. While ITS has made notable progress in personalised learning, further efforts are needed to enhance model generalisability, interpretability, and fairness. Addressing these challenges will be instrumental in developing inclusive, adaptive, and equitable learning environments, maximising the impact of ITS across diverse educational contexts.

Keywords: Intelligent Tutoring Systems (ITS), Student Performance Prediction, Hybrid Models, Educational Data Mining, Fairness in AI Education.

Received 26 January 2025. Accepted 21 March 2025.

For citation: Razali Y., Magagula A.K. (2025). Student Performance Prediction in Intelligent Tutoring Systems: Methods, Challenges, and Future Perspectives. *Ilim* 43(1). 18-34.

Introduction

Predicting students' academic performance is becoming more and more significant in educational research because it ensures timely interventions that can enhance learning outcomes and lower student failure. The current educational era, characterised by increasing enrolment and the growing use of online, blended, and e-learning models, has made it more challenging to predict students' academic success (Brdesee et al., 2022: 1-21). Using Internet technologies in the classroom has both benefits and drawbacks, particularly when it comes to anticipating and understanding unique learning paths in diverse contexts. As a remedy for these issues, intelligent tutoring systems, or ITSs, have emerged, enhancing the efficiency and personalisation of the learning process.

According to (Chaturvedi and Ezeife 2017: 168-175), intelligent tutoring systems (ITS) are advanced computer programs that offer tutoring to students in a range of subjects without requiring a teacher to be physically present. These systems provide continuous assessment and adaptive personalisation of learning experiences, making education more effective and inclusive for diverse learners (Greeni et al. 2024). One of the primary challenges in ITSs is still accurately predicting student performance, which necessitates managing a variety of variables like academic history, engagement metrics, and changing behaviours over time in order to support timely and effective interventions (Roy and Farid, 2024: 75577-75598). With ITS being integrated into more and more educational contexts, predictive accuracy is crucial for enhancing learning outcomes and providing focused support.

Machine learning and data mining methods have emerged as viable solutions to performance prediction issues in ITS. In particular, deep learning algorithms have demonstrated promising outcomes in forecasting student performance at intermediate stages of an online course delivery, according to (Moubayed et al. 2023). Intelligent tutoring can become more flexible and responsive by utilising techniques like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models, which have been shown to increase the accuracy of student performance predictions. Predictive models enable ITS to track students' evolving knowledge states, enabling real-time delivery of tailored learning resources and fostering more fruitful learning outcomes (Schmucker et al., 2021: 1-44).

However, despite significant advancements, there are still significant gaps in the interpretability, generalisability, and fairness of the models. Many of the existing models, which work well in specific contexts, lack the scalability required to succeed across different educational systems (Aljohani et al. 2019: 1-12; Brdesee et al. 2022: 1-21; Rajendran et al. 2022: 1-15; Thamilselvan et al. 2024). Furthermore, because some predictive models, particularly those based on deep learning, are complex, it can be challenging to understand and explain predictions in a way that stakeholders and educators can easily understand (Pek et al. 2023: 1224-1243; Soyoye et al. 2023: 431-434; Zhen et al. 2023: 12-29). Ensuring fairness is another concern because biassed data or model design can result in unfair outcomes for under-represented student groups (Khan et al. 2023: 86953-86962; Pek et al. 2023: 1224-1243; Abdalkareem and Min-Allah 2024: 30604-30626; Raji et al. 2024: 23595-23612).

The purpose of this review is to assess existing methods for predicting student performance in Intelligent Tutoring Systems (ITS) in order to identify current challenges. It also examines recent advancements and creative methods to enhance predictive analytics, providing direction for further study and implementation. By addressing both the positive aspects as well as drawbacks of current models, the review promotes data-driven, inclusive, and adaptive learning environments that maximize ITS capabilities.

A comprehensive review of studies published between 2019 and 2024 was conducted using data from reliable databases like IEEE Xplore, Scopus, ScienceDirect, and SpringerLink. By using specific keywords such as "multimodal data analytics," "AI in education," and "student performance prediction," pertinent research using AI-driven methods was found. Methodologies integrating artificial intelligence (AI) or machine learning (ML), their suitability for educational settings, and the reliability of their data analysis were given priority in the inclusion criteria.

The selected studies were categorized based on methodologies, datasets, and evaluation metrics. Techniques included sophisticated deep learning and ensemble methods like CNN-LSTM, Reinforcement Learning with Contextual Human Input (RLCHI), and Hybrid Deep Learning (HDL), as well as more conventional models like Random Forest and Support Vector Machine (SVM). Datasets included sources like Learning Management System (LMS) logs, the Open University Learning Analytics Dataset (OULAD), and multimodal data from ITS, which combined a variety of features like behavioural metrics and sociodemographic characteristics. Accuracy, AUC-ROC, and fairness measures were among the evaluation metrics; model transparency and interpretability were improved by tools like SHAP and LIME. The review provides a roadmap for creating more efficient, fair, and broadly applicable predictive models in education by identifying important trends and obstacles through this synthesis.

Literature Review

The use of machine learning and deep learning techniques to predict student performance has been thoroughly investigated. In academic and behavioural contexts, traditional models like Random Forest, Decision Trees, and Support Vector Machines have proven to have strong predictive capabilities (Abdalkareem and Min-Allah 2024: 30604-30626; Thamilselvan et al. 2024:). In a variety of educational applications, deep learning architectures such as CNNs, RNNs, and hybrid CNN-LSTM models have demonstrated exceptional promise in capturing intricate temporal and feature interaction patterns with high accuracy (Liu et al. 20221-19; Alnasyan et al. 2024: 1-29).

Multimodal data integration and feature selection have played a major role in improving model robustness.

Techniques like Bayesian Knowledge Tracing and Adaptive Feature Selection have increased the relevance of predictive features, while multimodal approaches that integrate ITS logs and engagement metrics have broadened the scope of predictive analytics (Chango et al. 2021: 614-634; Almarzuki et al. 2024: 247-256). Dimensionality reduction methods like PCA and t-SNE have further facilitated the integration of high-dimensional socio-behavioral data (Thamilselvan et al. 2024).

Prediction accuracy and fairness have significantly increased thanks to developments in ensemble learning, such as stacked models and hybrid architectures. Context-specific modelling has improved adaptability to specific courses and student profiles by utilising psychological metrics and LMS activity logs (Khan et al. 2023; Xu and Sun 2023). Still, there are problems with data imbalances, computational demands, and generalisability that necessitate advancements in fairness-aware modelling and scalable AI frameworks (Hassan et al. 2020; Zong et al. 2023).

While showcasing the progress made in applying state-of-the-art AI techniques to predict student performance, the literature also highlights the need for more equitable, interpretable, and generalizable models.

Materials and Methods

Student Performance Prediction in Intelligent Tutoring Systems. Deep Learning Techniques.

Deep learning models, which use temporal and feature interaction data, consistently outperform traditional methods in predicting student outcomes. These mechanisms have been utilised by CNN-LSTM and Feature-Stacked Neural Networks (FSNN) to attain a noteworthy degree of accuracy (Liu et al. 2022; Alnasyan et al. 2024). Furthermore, for improved interpretability and accuracy, teacher feedback has been incorporated into Reinforcement Learning with Contextual Human Input (RLCHI), which has also made notable strides (Vimarsha et al., 2024: 436-446). CNN and RNN-LSTM models have proven especially successful in online course prediction, with accuracy rates as high as 91% for Middle Eastern datasets (Moubayed et al. 2023).

Ensemble Learning Approaches

Ensemble learning models demonstrated remarkable performance in a range of prediction tasks, including student retention predictions and high-stakes exams. With accuracy levels of 92.18% and an AUC of 0.983, Random Forest (RF) and stacked ensembles have demonstrated remarkable success in forecasting high-stakes exams and dropout risks (Niyogisubizo et al., 2022: 1-12). Ensemble classifiers, such as AdaBoost and Gradient Boosting, have also demonstrated remarkable efficacy in handling unbalanced datasets and improving predictive accuracy (Hassan et al., 2020: 1-8). A hybrid stacking model that combined algorithms like RF, Decision Tree, KNN, and AdaBoost was able to predict at-risk students in Turkey with 98.4% accuracy, demonstrating the impressive performance of hybrid ensemble stacking models (Pek et al., 2023: 1224-1243).

Hybrid Approaches and Feature-Enhanced Models

Hybrid methods have been used to improve model adaptability and performance. A Gradient-Boosted Neural Network (GBNN) outperformed other deep learning techniques in predicting learning outcomes (Farhood et al., 2024: 1-17). Similarly, (Almarzuki et al., 2024: 247-256) enhanced Bayesian Knowledge Tracing (BKT) by incorporating confidence parameters, which resulted in improved RMSE values in ITS datasets. Combining traditional ML methods with feature optimisation, Adaptive Feature Selection Algorithm (AFSA) achieved up to 22% higher accuracy compared to existing methods (Roy and Farid, 2024: 75577-75598).

Interpretable Models

Interpretability-focused models have shown promise in supporting educators. Decision Tree (DT) models have shown particular utility in the use of demographic and performance data for academic monitoring (Allam et al., 2023: 215-219). The efficacy of flexible feature selection techniques was demonstrated by (Al-Zawqari et al., 2022: 1-14), who eliminated the need for manual feature engineering and achieved 93% predictive accuracy. In a different study, the Owl Search Optimised Dynamic Deep Neural Network (OSO-DDNN) integrated psychological traits like individualism and self-esteem to achieve a 92% accuracy rate (Deng et al., 2024: 1-8).

Clustering and Regression Techniques

Clustering methods such as K-Means have proven effective in categorizing students based on performance. For instance, clustering approaches have classified students into high, average, and low-performing groups, revealing patterns of academic success across socio-demographic profiles (Tsygankov et al., 2023: 325-327). Regression models, including Multiple Linear Regression (MLR) and Support Vector Regression (SVR), have also been utilised. SVR with a linear kernel achieved the highest R^2 score of 83.44% for predicting student performance (Dabhade et al., 2021: 5260-5267).

Applications in Multimodal Data Fusion

Multimodal data fusion has emerged as a promising avenue for predictive analytics in ITS. Studies integrating ITS logs, eye-tracking data, and facial emotion analysis have achieved high accuracy, with REPTree-based ensemble methods attaining an accuracy of 87.5% and an AUC of 0.88 (Chango et al., 2021: 614-634). Advanced applications, such as NLP for grading descriptive answers and web crawling for personalised study material recommendations, further exemplify the innovative use of multimodal data (Tharsha et al., 2021: 305-310).

Targeted Applications and Pathway Predictions

Specific applications for academic pathway prediction have shown the potential of advanced ML models. (Abdalkareem and Min-Allah, 2024: 30604–30626) demonstrated that Random Forest achieved 99% accuracy in predicting future academic pathways for Saudi high school students, with significant predictors including Physics and Mathematics grades. In engineering education, Artificial Neural Networks (ANNs) achieved accuracy rates of 71.5% to 74.1% for early performance predictions (Ghashout et al., 2023: 40-45).

Critical Predictors

a. Academic Metrics

Academic features, particularly grade point average (GPA) and grades in core subjects, consistently emerged as significant predictors of student performance. Studies highlighted the impact of high school grades, continuous assessment scores, and subject-specific grades, such as Mathematics and Chemistry, on academic outcomes (Mastour et al. 2023; Moubayed et al. 2023; Ballestar et al. 2024). Derived features like Maximum GPA and Average Credits per Semester were also influential in several contexts, indicating the role of cumulative and semester-level performance in prediction models (Arqawi et al. 2022; Alija et al. 2023). Process assessment scores were particularly emphasized, accounting for 60% of final grades in certain datasets (Li, 2023: 403-409).

b. Behavioural Engagement

Behavioural metrics, such as login counts, resource views, and participation in learning activities, were shown to be crucial for predicting academic outcomes. For instance, cumulative GPA (CGPA) combined with behavioural features like login counts significantly enhanced prediction accuracy (Hassan et al., 2020: 1–8). Attendance was a consistently strong predictor, with studies correlating high attendance rates and active engagement with better academic performance (Tharsha et al. 2021; Soyoye et al. 2023). LMS activity metrics, including total active days, sessional activities, and interaction patterns, further reinforced the importance of temporal engagement in identifying at-risk students (Brdesee et al. 2022; Khan et al. 2023).

c. Psychological Attributes

Psychological factors such as perceived stress, resilience, and confidence levels also played a vital role in academic performance prediction. Resilience acted as a mitigating factor for stress, while high engagement unexpectedly amplified the adverse effects of stress on GPA, illustrating the complex interplay between these variables (Tormon et al. 2023, pp.1-11). Positive emotional states, such as surprise, were linked to academic success, particularly in intelligent tutoring systems (Chango et al., 2021: 614-634). Additionally, self-esteem and individualism were found to influence academic outcomes, as demonstrated in deep learning models incorporating psychological attributes (Deng et al., 2024: 1-8).

d. Demographic and Socio-Economic Factors

Demographic attributes, including parental education, family size, school type, and location, were frequently cited as impactful predictors. For instance, school type and location were significant in predicting future academic pathways for Saudi high school students (Abdalkareem and Min-Allah, 2024: 30604-30626). Studies also found limited influence of socio-demographic variables like gender and academic level, with lifestyle metrics and behavioural attributes proving more predictive in certain cases (Rajendran et al., 2022: 1-15).

e. Physical Fitness

Physical fitness attributes, such as upper limb strength, aerobic endurance, and trunk strength, positively correlated with academic performance, particularly among younger students. Conversely, higher body mass index (BMI) was negatively associated with academic outcomes, highlighting the potential role of fitness in educational success (Xu and Sun 2023).

f. Cognitive and Interaction Features

Cognitive attributes, such as pre-test ranks and cognitive dialogue types, emerged as important predictors in classroom settings. Interaction patterns within virtual learning environments (VLEs) were also influential, with activity types like quiz attempts and forum engagements being key indicators of at-risk students (Aljohani et al. 2019; Zhen et al. 2023). Coordination of information sources and summarisation frequency further enhanced prediction accuracy in ITS (Chango et al., 2021: 614-634).

g. Program-Specific Predictors

Program-specific datasets provided insights into predictors of degree-level outcomes. Past GPA and individual course grades were the most significant predictors for identifying at-risk students (Pek et al., 2023: 1224-1243). Additionally, general core course grades, programme preferences, and field-specific academic performance were critical in predicting outcomes in higher education contexts (Ravi Kiran et al. 2023).

Common critical predictors for students' academic performance include academic, behavioural, psychological, demographic, and physical fitness domains. These predictors, which were found in a variety of machine learning models, highlight how crucial it is to incorporate a range of characteristics in order to facilitate early interventions and successfully support individualized teaching methods.

Results and Discussion

Challenges and Future Directions. Challenges in Current Methodologies.

Several challenges persist in methodologies for predicting student performance, including data sparsity, imbalances, computational limitations, and the integration of diverse features. Issues related to model interpretability and demographic biases also remain significant (Liu et al. 2022; Nachouki et al. 2023; Deng et al. 2024; Farhood et al. 2024; Masood et al. 2024; Roy and Farid 2024). A common challenge is the trade-off between computational efficiency, fairness, and interpretability, particularly in complex deep learning models (Zong et al. 2023; Vimarsha et al. 2024). For instance, (Alshaikh and Hewahi, 2024: 239-258) underscored the need for improved techniques to manage imbalanced datasets, while (Ghashout et al., 2023: 40-45) identified class imbalance as a key limitation affecting artificial neural networks (ANN).

Data Imbalances

Handling imbalanced datasets remains a pervasive issue, necessitating innovative approaches. Techniques such as Synthetic Minority Oversampling (SMOTE) have been widely used but often lead to risks of overfitting, requiring integration with methods like Edited Nearest Neighbours (ENN) for improved stability (Hassan et al., 2020). In another work, (Raji et al., 2024: 23595-23612) highlighted the use of synthetic data to address imbalances in datasets for Deaf and Hard of Hearing (DHH) students, improving accuracy but raising concerns about data reliability. Similarly, (Abdalkareem and Min-Allah, 2024: 30604–30626) leveraged SMOTE to balance datasets for predicting academic pathways, while (Chango et al., 2021: 614-634) emphasised the importance of preprocessing multimodal data to manage heterogeneity and dimensionality.

Computational Challenges

High-dimensional datasets and computational inefficiencies are recurring obstacles. Applying techniques like Genetic Algorithms (GA) to optimise models for large datasets presents significant demands on computational resources (Nagarajan et al. 2024). Similarly, (Ali et al., 2023: 101-105; Li, 2023: 403-409) faced challenges in managing high-dimensional data, requiring extensive preprocessing and feature selection to improve model performance. Temporal data, which often necessitates complex preprocessing to capture meaningful patterns without overfitting, adds another layer of complexity.

Generalisation and Dataset Scope

The limited scope and generalisability of datasets constrain the broader applicability of predictive models. Studies such as those by (Xu and Sun 2023) and (Tormon et al. 2023, pp.1-11) reported small sample sizes as limiting factors, while self-selection biases further affected the robustness of findings. In their study, (Rajendran et al., 2022: 1-15) noted limited variability in socio-economic data, which reduced the generalisability of their models, and (Zhen et al., 2023: 12-29) found moderate improvements over baseline accuracy, indicating the need for more complex feature engineering.

Dataset Size and Class Balancing

Balancing dataset classes is a persistent issue in educational data mining. Techniques like SMOTE have been used to address imbalances but require careful application to avoid overfitting (Brdesee et al. 2022; Pek et al. 2023). Managing sequential data poses unique challenges, as varying time intervals in interactions complicate early identification of at-risk students (Aljohani et al., 2019: 1-12). Large-scale datasets, such as those spanning multiple courses, necessitate tailored approaches to maintain accuracy while handling diverse and heterogeneous data (Khan et al., 2023: 86953-86962).

Emerging Trends and Innovations

a. Hybrid and Ensemble Models

Hybrid approaches and ensemble techniques are emerging as leading innovations in student performance prediction. Methods such as dynamic feature selection, ensemble voting classifiers, and collaborative frameworks have enhanced predictive accuracy and model robustness (Al-Zawqari et al. 2022; Ahmed 2024; Almarzuki et al. 2024). These approaches integrate demographic, psychological, and behavioural data to enable personalised learning strategies (Alhazmi and Sheneamer 2023; Alshaikh and Hewahi 2024).

b. Dimensionality Reduction and Preprocessing

Dimensionality reduction techniques like t-SNE are increasingly used to integrate socio-behavioural data into predictive models, improving their interpretability and utility (Thamilselvan et al. 2024). Preprocessing techniques, including grid search hyperparameter tuning, have also demonstrated significant improvements in model accuracy by ensuring balanced and comprehensive data integration (Soyoye et al., 2023: 431-434).

c. Multimodal Data Integration

Integrating multimodal data sources, such as ITS logs, eye-tracking metrics, and emotional recognition, has proven effective in enhancing feature selection and improving predictive accuracy. This trend underscores the reliability of using numerical data over discretised formats for robust predictions (Chango et al., 2021: 614-634). Additionally, natural language processing (NLP) innovations, such as automatic grading and personalised material recommendations, offer unified academic support systems (Tharsha et al., 2021: 305-310).

d. Advanced Architectures and AI Applications

The use of advanced architectures, such as hybrid CNN-RNN models, highlights the potential for combining deep learning with traditional machine learning to process sequential and spatial data effectively (Ali et al., 2023: 101-105). Similarly, Long Short-Term Memory (LSTM) networks have been instrumental in capturing long-term dependencies in student engagement data, particularly in virtual learning environments (Aljohani et al. 2019; Brdesee et al. 2022). Real-time prediction applications, such as those using hybrid stacking models, are also emerging as practical tools for educational data mining (Pek et al., 2023: 1224-1243).

e. Physical and Psychological Metrics

The integration of physical fitness metrics, including body strength and aerobic endurance, is an innovative addition to predictive models for younger students (Xu and Sun 2023). Psychological factors, such as resilience and stress mitigation, are also gaining prominence, with studies advocating resilience training to counteract the adverse effects of stress on academic performance (Tormon et al. 2023, pp.1-11).

Caveats and Future Research Directions

a. Scalability and Dataset Diversity

A primary limitation of current methodologies is their scalability across diverse educational contexts. Future research should prioritize validating models on larger, more varied datasets to enhance generalizability (Alija et al. 2023; Gonzalez-Nucamendi et al. 2023). Additionally, adaptive resampling and data augmentation methods should replace traditional oversampling techniques to handle imbalanced datasets more effectively (Adewale et al., 2024: 1-20).

b. Enhancing Interpretability

Deep learning models often suffer from a lack of interpretability, which limits their adoption in educational settings. Explainable AI (XAI) techniques like SHAP and LIME should be further developed to provide intuitive insights for non-technical stakeholders (Schmucker et al. 2021; Masood et al. 2024). Advanced AI models, including GPT and other transformers, offer opportunities for handling complex, multimodal data and real-time analytics (Spitzer et al., 2024: 1-26).

c. Fairness and Bias Mitigation

Ensuring fairness in predictions remains critical, as demographic biases can lead to inequities in student outcomes. The adoption of fairness-aware modelling techniques, such as DebiasEdu frameworks and fairness metrics during model evaluation, is crucial for equitable outcomes (Zong et al., 2023: 198-210).

d. Broader Contexts and Data Inputs

Expanding datasets to include behavioural, psychological, and socio-economic factors is a vital step forward. This includes integrating teacher-student interaction metrics and longitudinal data for more comprehensive predictive models (Zhen et al., 2023: 12-29). Additionally, refining methodologies for underrepresented student groups and diverse academic disciplines can enhance inclusivity and applicability (Rajendran et al. 2022; Ali et al. 2023).

e. Optimising Computational Efficiency

Research should also focus on improving computational efficiency for high-dimensional datasets. Techniques such as advanced neural networks and clustering methods must be adapted to handle the complexities of large-scale educational data (Nagarajan et al. 2024; Thamilselvan et al. 2024). By addressing these challenges and leveraging emerging trends, future research can significantly enhance the robustness, scalability, and fairness of predictive models, driving innovations in educational data mining and personalised learning strategies.

Conclusion

This review highlights the significant strides made in predictive models for Intelligent Tutoring Systems (ITS), showcasing the effectiveness of hybrid and ensemble approaches, such as RLCHI and CNN-LSTM, in enhancing prediction accuracy and personalisation. Advanced feature engineering techniques and the integration of multimodal data have further enabled ITS to adapt to diverse learning needs, demonstrating their transformative potential in education. However, challenges persist in generalisability, interpretability, data quality, and fairness. Most models perform well in specific contexts but struggle with scalability across diverse educational environments. Techniques like SMOTE address data imbalances but risk introducing noise, while deep learning models offer high accuracy at the expense of transparency. Tools like SHAP and LIME provide some interpretability, but more intuitive solutions are required for educators to fully trust AI-driven decisions. Ensuring fairness and mitigating demographic biases remain pivotal. Future advancements must prioritize inclusive and equitable model development, validate across diverse datasets, and integrate richer socio-demographic and behavioural data. By addressing these challenges, ITS can evolve into a cornerstone of adaptive, data-driven, and ethical education systems, supporting personalised and equitable learning experiences for all students.

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Разали Иаакоб[1], Магагула Алсон Хумбулани[2]
[1]Қауымдастырылған профессор, PhD, [2]Магистрант
[1, 2] Малайзия Путра университеті. Сердан/Малайзия.

Зияткерлік репетиторлық жүйелердегі студенттердің өнімділігін болжау: әдістер, қиындықтар және болашақ перспектива

Аңдатпа. Интеллектуалды репетиторлық жүйелерде (ITS) болжамды модельдерді қолдану жекелендірілген оқытуды жақсартуға және тәуекел тобындағы студенттерді ерте анықтауға мүмкіндік беретін маңызды жетістіктерге қол жеткізді. Дегенмен, үлгінің жалпылануы, интерпретациялануы, деректер сапасы және әділдігімен байланысты қиындықтар сақталып, олардың әртүрлі білім беру орталарында кеңінен қолданылуын шектейді. Бұл шолу IEEE Xplore, Scopus, Science Direct, Google Scholar және SpringerLink сияқты дерекқорлардан алынған 2019 және 2024 жылдар аралығында жарияланған 58 зерттеудің нәтижелерін синтездейді. Әдебиеттерді таңдау «оқушылардың үлгерімін болжау» және «білімдегі AI» сияқты түйінді сөздерге негізделген. Әдістемелер, деректер жиыны және бағалау көрсеткіштері тақырыптық трендтерді анықтау және ITS үшін қиындықтар мен мүмкіндіктерді көрсету үшін санатталған. Нәтижелер гибридті модельдер (мысалы, CNN-LSTM, RLCHI), ансамбльді оқыту және мультимодальды деректерді біріктіру болжамдық өнімділікті айтарлықтай жақсартатынын көрсетеді. SHAP және LIME сияқты әдістер түсіндіру мүмкіндігін жақсартты, ал әлеуметтік-демографиялық және мінез-құлық деректерін қамтитын модельдер оқушылардың оқу үлгілері туралы жақсырақ түсінік береді. Осыған қарамастан, жалпылау және әділдік әртүрлі деректер жинақтарын және әділдікке негізделген модельдеу тәсілдерін талап ететін негізгі қиындықтар болып қала береді. ITS жекелендірілген оқытуда айтарлықтай жетістіктерге жеткенімен, модельдің жалпылануын, түсіндірмелілігін және әділдігін арттыру үшін қосымша күш салу қажет. Бұл міндеттерді шешу әртүрлі білім беру контексттерінде ITS әсерін барынша арттыра отырып, инклюзивті, бейімді және тең оқу орталарын дамытуда маңызды рөл атқарады.

Кілт сөздер: Интеллектуалды репетиторлық жүйелер (ITS), студенттердің өнімділігін болжау, аралас модельдер, білім беру деректерін іздеу, AI біліміндегі әділдік.

Разали Иаакоб[1], Магагула Алсон Хумбулани[2]
[1]Ассоциированный профессор, PhD, [2]Магистрант.
[1, 2] Малазийский университет Путра. Серданг/Малайзия.

Интеллектуальные системы обучения (ИСО), прогнозирование успеваемости учащихся, гибридные модели, интеллектуальный анализ образовательных данных, справедливость в образовании с использованием искусственного интеллекта

Абстракт. Применение прогностических моделей в интеллектуальных системах обучения (ITS) значительно продвинулось вперед, улучшив персонализированное обучение и раннее выявление учащихся из группы риска. Однако проблемы, связанные с обобщаемостью моделей, интерпретируемостью, качеством данных и справедливостью, сохраняются, что ограничивает их широкое внедрение в различных образовательных средах. В этом обзоре обобщены результаты 58 исследований, опубликованных в период с 2019 по 2024 год, полученные из таких баз данных, как IEEE Xplore, Scopus, Science Direct, Google Scholar и SpringerLink. Выбор литературы основывался на таких ключевых словах, как «прогнозирование успеваемости учащихся» и «ИИ в образовании». Методы, наборы данных и метрики оценки были классифицированы для выявления тематических тенденций и выделения проблем и возможностей для ITS. Результаты показывают, что гибридные модели (например, CNN-LSTM, RLCHI), ансамблевое обучение и интеграция мультимодальных данных значительно повышают прогностическую эффективность. Такие методы, как SHAP и LIME, улучшили интерпретируемость, в то время как модели, включающие социально-демографические и поведенческие данные, обеспечивают лучшее понимание моделей обучения студентов. Тем не менее, обобщаемость и справедливость остаются ключевыми проблемами, требующими разнообразных наборов данных и подходов к моделированию, учитывающих справедливость. Хотя ITS добилась заметного прогресса в персонализированном обучении, необходимы дальнейшие усилия для повышения обобщаемости, интерпретируемости и справедливости моделей. Решение этих проблем будет иметь решающее значение для разработки инклюзивных, адаптивных и справедливых учебных сред, максимизируя влияние ITS в различных образовательных контекстах.

Ключевые слова: интеллектуальные системы обучения (ITS), прогнозирование успеваемости студентов, гибридные модели, интеллектуальный анализ образовательных данных, справедливость в образовании с использованием искусственного интеллекта.