STUDENT PERFORMANCE CLASSIFICATION IN E-LEARNING: INSIGHTS FROM PREDICTIVE LEARNING ANALYTICS AND MACHINE LEARNING

Loveny Jekul[1], Jackel Vui Lung Chew[2]

Faculty of Computing and Informatics, Universiti Malaysia Sabah
jackelchew93@ums.edu.my

Received: 4.11.2025 Accepted: 21.11.2025
Revised: 28/11/2025 Published: 4.12.2025
DOI: https://doi.org/10.51200/ijelp.v8i1.6807

Abstract

Predictive learning analytics has emerged as a critical research area in educational technology, integrating machine learning, data mining, and statistical modelling to forecast student outcomes and inform timely interventions. Building on the traditions of educational data mining and learning analytics, predictive learning analytics leverage large-scale learner datasets generated from learning management systems and massive open online courses. This paper conducts a short review of predictive learning analytics studies published between 2021 and 2025, following PRISMA 2020 guidelines. From an initial set of 35 records retrieved through Google Scholar, 10 studies were selected based on defined inclusion criteria. A taxonomy of predictive learning analytics research is developed across four dimensions namely study objectives, techniques, learning environments, and evaluation metrics. This paper reveals four dominant objectives which are early identification of at-risk students, performance prediction, personalised learning support, and institutional decision support. Methodologies span traditional machine learning workflows, deep learning architectures, hybrid models, and system-level frameworks. Notable applications include early warning systems, personalised intervention platforms, and institutional dashboards. However, several challenges persist, including fragmented datasets, limited generalisability, lack of interpretability in deep learning models, privacy and ethical concerns, and inconsistent evaluation practices. This paper highlights PLA's potential to enhance student retention, personalised instruction, and institutional planning when applied responsibly. This paper concludes with recommendations for educators, emphasising the adoption of explainable models, integration of diverse learner data, and development of course-agnostic approaches to improve scalability and trust in predictive systems.

Keyword(s): *e-learning, predictive learning analytics, machine learning, student performance, classification*

INTRODUCTION

Predictive Learning Analytics (PLA) has emerged as a significant research area within educational technology, combining machine learning (ML), data mining (DM), and statistics to forecast and predict student outcomes (Namoun and Alshanqiti, 2020; Sharma et al., 2023). PLA builds on the foundations of Educational Data Mining (EDM) and Learning Analytics (LA), which leverages large-scale learner data generated in online platforms such as Learning Management Systems (LMS) and Massive Open Online Courses (MOOCs) (Alhothali et al., 2022; Pan et al., 2025).

The increasing adoption of MOOCs and other e-learning environments has generated immense interaction datasets. These phenomena demand effective PLA for identifying at-risk students, supporting adaptive interventions, and enabling scalable learning personalisation (Rizwan et al., 2025). However, these phenomena also present challenges to institutions such as high dropout rates and low retention rates, which threaten the effectiveness of online learning (Rizwan et al., 2025). Effective PLA models can mitigate such risks by enabling timely interventions that improve student outcomes and institutional planning.

Although many studies have explored PLA, the research landscape remains fragmented. Prior reviews highlighted diverse methodologies, datasets, and evaluation metrics, with no universal consensus on the most effective algorithms or features (Pan et al., 2025). For example, Alhothali et al. (2022) reviewed ML and deep learning (DL) methods for predicting student outcomes in MOOCs, focusing on dropout and performance prediction, while Sghir et al. (2022) provided a decade-long review (2012–2022) on modeling processes and evaluation criteria. More recently, Rizwan et al. (2025) systematically reviewed factors affecting academic performance and engagement in MOOCs using DL, emphasizing behavioural and clickstream data alongside demographic and academic features.

Despite these contributions, gaps remain in synthesising findings across recent years (2021–2025). To address this gap, this paper conducts a short review of PLA studies between 2021 and 2025, following the PRISMA 2020 guidelines (Page et al., 2021). A total of 35 records were retrieved from Google Scholar using the keyword string of "e-learning" AND "predictive learning analytics" AND "machine learning" AND "student performance" AND "classification" AND "OULAD", of which 10 met the inclusion criteria after screening. This paper categorises PLA by study objectives, techniques, learning environments, and evaluation metrics, and further discusses methodologies, applications, challenges, and directions for future research.

The remainder of this paper is structured as follows. Section 2 outlines the background of PLA. Section 3 develops a taxonomy of PLA studies based on objectives, techniques, environments, and metrics. Section 4 examines methodologies and applications. Section 5 discusses challenges and limitations. Finally, the conclusion provides recommendations for educators.

BACKGROUND OF PREDICTIVE LEARNING ANALYTICS

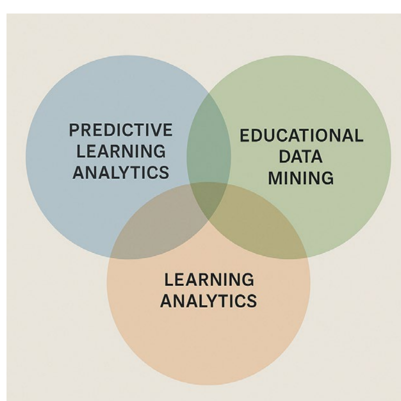

Figure 1: Relationship between predictive learning analytics, education data mining and learning analytics.

As shown in Figure 1, the origins of PLA are closely tied to the evolution of EDM and LA. EDM, which gained prominence in the early 2000s, primarily focused on discovering patterns in educational data to support instructional design (Sghir et al., 2022). PLA extends this by applying predictive models that forecast and predict student outcomes, thereby offering actionable insights for proactive interventions that can be taken by institutions (Pan et al., 2025).

PLA's rise is also a response to the rapid digitalisation of education especially after the COVID-19 pandemic. Online learning platforms such as MOOCs and LMS generate extensive behavioural, demographic, and academic datasets (Alhothali et al., 2022; Rizwan et al., 2025). While EDM emphasises algorithmic discovery of hidden patterns, PLA is oriented toward decision-making based on prediction and forecasting. PLA is also operationalised in early warning systems that allow educators to intervene before education failure occurs (Pan et al., 2025).

Thus, PLA represents another circle and intersects with EDM's pattern-discovery tradition and LA's decision-support orientation. These three areas aim to improve retention, personalise instruction, and optimise institutional strategies. Its relevance continues to grow with the expansion of online education and the availability of benchmark datasets such as the Open University Learning Analytics dataset (OULAD), which facilitate reproducibility and cross-study comparisons (Pan et al., 2025; Rizwan et al., 2025).

TAXONOMY OF PREDICTIVE LEARNING ANALYTICS

The recent studies on PLA demonstrate a wide diversity of approaches, which can be categorised along four dimensions such as objectives, techniques, learning environments, and evaluation metrics. This section provides an analytical lens to compare studies and highlight common practices as well as gaps.

Objectives

There are four objectives that PLA studies commonly pursue. Firstly, identifying at-risk students. Many studies prioritise the earliest possible detection of learners likely to fail or withdraw. For example, Adnan et al. (2021) used the OULAD dataset to predict dropout risk at different percentages of course completion. They suggested that random forest model is the most effective model for early intervention.

Secondly, predicting performance and grades. Al-Azazi and Ghurab (2023) developed an ANN-LSTM model, which is the combination of artificial neural network and long short-term memory, for a multi-class prediction (distinction, pass, fail, withdrawn) in MOOCs.

Thirdly, personalising learning support. PLA systems increasingly aim to tailor interventions by modelling behavioural and emotional dimensions. Kukkar et al. (2024) introduced a hybrid of recurrent neural network, long short-term memory feature selection and ML approach using academic, demographic, and emotional data to improve personalised prediction accuracy.

Finally, institutional decision support. Beyond individual-level forecasting, some research integrates PLA into data-driven educational management. Abdul Rahim et al. (2024) introduced data lake architecture to unify student information and LMS logs, enabling scalable prediction and supporting administrative decision-making.

Techniques

PLA employs a wide range of ML and DL methods. Traditional ML models such as decision trees, Naïve Bayes, support vector machines, and k-nearest neighbours remain widely used in the experiments due to their interpretability and efficiency (Adnan et al., 2021; Abdul Rahim et al., 2024). Then, ensemble ML such as random forest and gradient boosting often outperform single traditional ML models, with studies reporting strong results in both early and final-stage predictions (Abdul Rahim et al., 2024).

Besides that, DL architectures like recurrent neural networks, long short-term memory, and hybrid ANN-LSTM models are gaining adoption for sequential and time-dependent student behaviour modelling. For instance, Al-Azazi and Ghurab (2023) and Kukkar et al. (2024) demonstrated superior accuracy when combining long short-term memory with ML classification models.

Moreover, there is a growing interest in hybrid frameworks. Integrating statistical methods, ML, and DL has been proposed to balance predictive power and explainability. Ahmadian Yazdi et al. (2022) emphasised combining interpretable ML models with deep architectures to address the trade-off between accuracy and transparency.

Learning Environments

PLA research spans diverse educational contexts. MOOCs are a dominant testbed, and current studies often rely on the OULAD dataset to benchmark prediction models (Adnan et al., 2021; Al-Azazi and Ghurab, 2023; Kukkar et al., 2024). Similarly, clickstream and engagement logs from LMSs such as Moodle and institutional platforms are also used for prediction models benchmarking (Abdul Rahim et al., 2024).

We also noticed that some studies integrate institutional data such as demographics, grades, enrolment records with LMS logs to provide a more holistic view of student behaviour and outcomes (Abdul Rahim et al., 2024). Then, PLA is increasingly linked with emotional and behavioural data to capture holistic learning profiles (Kukkar et al., 2024).

Evaluation Metrics

Performance evaluation in PLA relies on several common metrics. Accuracy is the most reported metric across studies, though limited in imbalanced datasets (Adnan et al., 2021). Then, precision, recall, and F1-score are frequently adopted to evaluate early detection of at-risk students, especially where false negatives carry higher consequences (Abdul Rahim et al., 2024). Additionally, macro and micro F1-scores are used in multi-class settings to balance class-level and instance-level performance reporting (Al-Azazi and Ghurab, 2023).

METHODOLOGIES AND APPLICATIONS

PLA methodologies can be classified into ML workflows, DL architectures, hybrid approaches, and system-level frameworks.

Machine Learning Workflows

Traditional ML remains widely adopted due to interpretability and computational efficiency. Adnan et al. (2021) applied multiple ML algorithms to the OULAD dataset for predicting student performance at different percentages of course length. Their experiments showed that random forest consistently outperformed most traditional classifiers, especially when integrating demographics, clickstream, and assessment features. Such workflows typically involve careful data preprocessing, splitting datasets for cross-validation, and evaluating performance using precision, recall, F1-score, and accuracy.

Deep Learning Architectures

DL models are increasingly employed for capturing sequential and time-dependent learning behaviours. Al-Azazi and Ghurab (2023) proposed a hybrid DL model that classifies learners into multi-class outcomes such as distinction, pass, fail, withdrawn in MOOCs. Their architecture achieved up to 72% accuracy by the end of the course. Similarly, Kukkar et al. (2024) combined recurrent neural network and long short-term memory with random forest to leverage both temporal dependencies and strong classification performance, achieving nearly 97% accuracy. These approaches highlight DL's ability to model complex interactions in educational datasets.

Hybrid and Ensemble Approaches

Recent methodologies emphasise blending ML and DL to balance predictive accuracy with interpretability. Kukkar et al. (2024) combined emotional and academic variables into a hybrid pipeline, while Ahmadian Yazdi et al. (2022) combined interpretable ML with DL to address the trade-off between transparency and performance. Ensemble learning techniques remain popular, especially in institutional-level prediction systems (Abdul Rahim et al., 2024).

System-Level Applications

Methodologies also extend to architectural frameworks. Abdul Rahim et al. (2024) developed a big data lake framework integrating LMS logs and institutional databases to support predictive dashboards and decision-making at scale. This demonstrates PLA's role beyond individual performance prediction, enabling institutional analytics for curriculum planning, resource allocation, and policy formulation.

In terms of application, PLA models have been successfully deployed in early warning systems, personalised intervention platforms, and institutional dashboards. Adnan et al. (2021) demonstrated how at-risk detection models can inform instructor interventions as early as 20% into the course. Al-Azazi and Ghurab (2023) showed how day-wise sequential prediction allows near real-time monitoring of student progress in MOOCs. Abdul Rahim et al. (2024) highlighted institutional applications where predictive insights inform administrators' decisions. These applications illustrate PLA's dual role which is supporting individual-level personalisation and system-level decision support.

CHALLENGES AND LIMITATIONS

Despite advancements, PLA faces persistent challenges that limit generalisability and adoption in real-world educational contexts. This section will discuss data quality and availability, generalizability across contexts, interpretability and transparency, ethical and privacy concerns, scalability and real-time processing, and evaluation practices.

Data Quality and Availability

Many studies highlight the difficulty of acquiring high-quality datasets. MOOCs and LMS datasets are commonly suffer from missing, noisy, or imbalanced records. Adnan et al. (2021) noted that demographic features alone yielded poor predictive performance and integration with behavioural and assessment data is required. Kukkar et al. (2024) also pointed out that emotional data is self-reported and difficult to standardise.

Generalisability Across Contexts

A recurring limitation is that models trained on specific courses may not generalise to new contexts. Al-Azazi and Ghurab (2023) emphasised that many predictive models overfit to course-specific structures. Even multi-class models trained on OULAD face reduced accuracy when applied to unseen courses. There is a need for course-agnostic and cross-domain approaches.

Interpretability and Transparency

While DL models offer high accuracy, they function as "black boxes." Ahmadian Yazdi et al. (2022) highlighted the importance of explainable artificial intelligence (AI) in PLA to ensure educators, students, and institutions can trust predictions. Without interpretability, adoption in sensitive educational decisions is constrained.

Ethical and Privacy Concerns

PLA relies on sensitive learner data such as demographics, behaviour logs, and emotional states. Kukkar et al. (2024) and Abdul Rahim et al. (2024) noted privacy constraints in collecting such data. Anonymisation and consent remain major issues, with many platforms hesitant to share datasets openly.

Scalability and Real-Time Processing

Although institutional frameworks such as Abdul Rahim et al.'s (2024) data lake show promise, real-time PLA applications remain technically challenging. The high computational cost of DL models like ANN-LSTM (Al-Azazi and Ghurab, 2023) and hybrid architectures (Kukkar et al., 2024) limits scalability in large-scale deployments.

Evaluation Practices

Last but not least, evaluation remains inconsistent across studies. Adnan et al. (2021) and Al-Azazi and Ghurab (2023) employed accuracy, precision, recall, and F1-score, but the imbalance in dropout versus completion classes always give skewed results. Macro and micro F1-scores address some issues, but standardised benchmarks are still lacking.

CONCLUSION AND RECOMMENDATIONS

Overall, PLA has rapidly evolved as a powerful approach to harness educational data for improving teaching, learning, and institutional decision-making. The reviewed studies demonstrate a wide range of methodologies, from traditional ML workflows (Adnan et al., 2021) to advanced DL architectures (Al-Azazi and Ghurab, 2023) and hybrid models (Kukkar et al., 2024). System-level frameworks, including data lake architectures (Abdul Rahim et al., 2024), illustrate PLA's capacity to support not only personalised learning interventions but also institutional analytics at scale.

While these methodologies achieve strong predictive performance, several limitations persist. Challenges such as fragmented datasets, poor generalisability across contexts, lack of interpretability, privacy concerns, and inconsistent evaluation metrics constrain large-scale adoption. Despite these barriers, this paper suggests that PLA can play a transformative role in higher education when deployed responsibly and strategically. Therefore, the following recommendations are offered for educators.

1) Educators should leverage PLA models for timely identification of at-risk students. Evidence shows that early detection, even within the first weeks of a course, enables targeted interventions that improve retention and success rates (Adnan et al., 2021).
2) While DL models provide high predictive performance, educators should prioritise models that offer explainable outputs to build trust with students and support transparent decision-making (Ahmadian Yazdi et al., 2022).
3) Combining demographics, behavioural logs, emotional factors, and assessment data provides a holistic view of learner progress (Kukkar et al., 2024; Abdul Rahim et al., 2024). Educators and administrators should collaborate to break down data silos between LMS, student information systems, and institutional records.
4) To overcome overfitting and enhance transferability, educators should adopt course-agnostic and multi-class predictive models that can generalise across diverse learning environments (Al-Azazi and Ghurab, 2023).

Co-Author Contribution

The authors declare no conflict of interest.

Ethics Statement

ChatGPT (OpenAI) was used solely to enhance the readability and linguistic clarity of this paper.

REFERENCES

Abdul Rahim, S. A., Sidi, F., Affendey, L. S., Ishak, I., & Nurlankyzy, A. Y. (2024). Leveraging data lake architecture for predicting academic student performance. International Journal on Advanced Science, *Engineering and Information Technology, 14*(6), 2121-2129. https://doi.org/10.18517/ijaseit.14.6.12408

Adnan, M., Habib, A., Ashraf, J., Mussadiq, S., Raza, A. A., Abid, M., ... & Khan, S. U. (2021). Predicting at-risk students at different percentages of course length for early intervention using machine learning models. *IEEE Access, 9*, 7519-7539. https://doi.org/10.1109/access.2021.3049446

Ahmadian Yazdi, H., Seyyed Mahdavi Chabok, S. J., & Kheirabadi, M. (2022). Dynamic educational recommender system based on improved recurrent neural networks using attention technique. *Applied Artificial Intelligence, 36*(1), 2005298. https://doi.org/10.1080/08839514.2021.2005298

Al-Azazi, F. A., & Ghurab, M. (2023). ANN-LSTM: A deep learning model for early student performance prediction in MOOC. *Heliyon, 9*(4), e15382. https://doi.org/10.1016/j.heliyon.2023.e15382

Alhothali, A., Albsisi, M., Assalahi, H., & Aldosemani, T. (2022). Predicting student outcomes in online courses using machine learning techniques: A review. *Sustainability, 14*(10), 6199. https://doi.org/10.3390/su14106199

Huang, Q., & Zeng, Y. (2024). Improving academic performance predictions with dual graph neural networks. *Complex and Intelligent Systems, 10*(3), 3557-3575. https://doi.org/10.1007/s40747-024-01344-z

Kukkar, A., Mohana, R., Sharma, A., & Nayyar, A. (2024). A novel methodology using RNN+ LSTM+ ML for predicting student's academic performance. *Education and Information Technologies, 29*(11), 14365-14401. https://doi.org/10.1007/s10639-023-12394-0

Namoun, A., & Alshanqiti, A. (2020). Predicting student performance using data mining and learning analytics techniques: A systematic literature review. *Applied Sciences, 11*(1), 237. https://doi.org/10.3390/app11010237

Rizwan, S., Nee, C. K., & Garfan, S. (2025). Identifying the factors affecting student academic performance and engagement prediction in MOOC using deep learning: A systematic literature review. *IEEE Access, 13*, 18952-18982. https://doi.org/10.1109/access.2025.3533915

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *British Medical Journal, 372*, n71.

Pan, J., Zhao, Z., & Han, D. (2025). Academic performance prediction using machine learning approaches: A survey. *IEEE Transactions on Learning Technologies, 18*, 351-368. https://doi.org/10.1109/tlt.2025.3554174

Sghir, N., Adadi, A., & Lahmer, M. (2023). Recent advances in predictive learning analytics: A decade systematic review (2012–2022). *Education and Information Technologies, 28*(7), 8299-8333. https://doi.org/10.1007/s10639-022-11536-0

Sharma, R., Shrivastava, S. S., & Sharma, A. (2023). Predicting Student Performance Using Educational Data Mining and Learning Analytics Technique. *Journal of Intelligent Systems and Internet of Things*, *10*(2), 24-37. https://doi.org/10.54216/JISIoT.100203