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Original Research Article

Learning Analytics and Predictive Modeling: Enhancing Student Success through Data-Driven Insights

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ABSTRACT
In the evolving landscape of data-informed education, predictive modeling has become a powerful tool for identifying students at risk of academic failure or withdrawal. This study investigates the use of learning analytics techniques to predict student outcomes using the Open University Learning Analytics Dataset (OULAD), a comprehensive, publicly available dataset that includes demographic profiles, continuous assessment records, and detailed interaction logs from a virtual learning environment (VLE). By integrating and preprocessing these data sources, the authors developed a comprehensive set of behavioral and temporal features, with particular focus on total click activity, which acts as a proxy for student engagement. The prediction task was framed as a binary classification problem: distinguishing students who completed a course (pass or distinction) from those who failed or withdrew. Although the specific classification algorithm is not explicitly identified, the trained model achieved a classification accuracy of 71% and an area under the receiver operating characteristic curve (ROC-AUC) of 0.79, indicating a reasonably high level of discriminative ability. A key strength of the study is its use of SHAP (Shapley Additive Explanations) values to interpret the model's output, offering transparency into how individual features influenced prediction results. The analysis showed that engagement-related features, especially VLE click counts, had the greatest predictive power, while demographic variables such as gender and age contributed little, suggesting a reduced risk of bias from protected attributes. These findings underscore the practical value of interpretable predictive models in supporting early warning systems and learner support strategies in higher education. Additionally, the study addresses important ethical considerations by emphasizing fairness, privacy, and the need for explainable AI. While some methodological limitations remain, such as the lack of algorithm disclosure and validation details, the research provides valuable insights into designing transparent, ethical, and actionable learning analytics tools.

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INTRODUCTION

The integration of machine learning (ML) and deep learning (DL) techniques into the educational landscape has witnessed a dramatic surge in recent years. These advancements are revolutionizing how educators, institutions, and policymakers understand, predict, and enhance student learning outcomes. Central to this transformation is the use of predictive analytics to anticipate key academic events ranging from student performance and engagement to retention and dropout risks based on increasingly rich and multidimensional data sources (Capuano et al., 2023a). Fueled by the ubiquity of digital learning environments and the rapid expansion of data availability, educational institutions now have access to a broad array of student-related data streams (Ahn et al., 2021). These include behavioral traces from Learning Management Systems (LMSs), academic performance records, demographic attributes, self-reported affective measures, and even physiological signals from wearable devices. The convergence of these data modalities allows for the development of sophisticated predictive models that not only diagnose academic issues but also proactively guide interventions, optimize instructional strategies, and personalize learning pathways. This evolution aligns with the broader shift in the fields of Learning Analytics (LA) and Educational Data Mining (EDM), which have transitioned beyond retrospective analysis to a predictive, decision-support paradigm (James et al., 2024). Predictive analytics, once a novel addition, has become a cornerstone in these disciplines, enabling early identification of at-risk students, fostering just-in-time support mechanisms, and informing institutional planning (Afzaal et al., 2021). In an era where educational ecosystems are increasingly complex, driven by the proliferation of online and hybrid modalities, widening learner diversity, and escalating performance accountability, the ability to forecast academic trajectories is more vital than ever. Across global higher education systems, longstanding challenges related to student retention, academic underperformance, and delayed graduation persist. For example, undergraduate attrition rates in some OECD countries exceed 45%, underscoring the urgent need for timely, data-driven strategies that support student success. Traditional reactive support models are often insufficient in addressing these multifaceted issues, particularly in digital and hybrid learning environments where early warning signals may be subtle or dispersed across platforms (Zhang & Xu, 2024). In response, LA has embraced the predictive potential of ML and AI to offer anticipatory solutions (G. Oise & Konyeha, 2024). From automated risk detection and real-time dashboards to adaptive feedback systems and personalized learning interfaces, these technologies are reshaping how education is delivered and experienced (Afzaal et al., 2021). As predictive analytics becomes more deeply embedded in institutional workflows, it promises not only to transform pedagogical practices but also to promote academic equity and operational efficiency. (Hwang & Tu, 2021)A foundational step in building effective predictive systems is the accurate identification of meaningful indicators of academic risk or success. These indicators fall into three broad categories: behavioral engagement metrics, academic performance data, and affective or socio-emotional factors. LMS interaction data, such as login frequency, resource views, and forum activity, serve as early proxies for engagement but may vary in predictive strength depending on the learning context (Albreiki et al., 2022). Recent findings suggest that *temporal engagement patterns,* such as consistency in study habits over time, provide more nuanced and reliable insights than aggregate metrics alone. Historical academic records, including cumulative GPA and standardized test scores, remain among the most robust predictors due to their ability to reflect long-term academic preparedness (Waheed et al., 2023a). Additionally, early formative assessments offer crucial insights into student progress during the initial weeks of a course, enabling preemptive support. Meanwhile, socio-emotional indicators such as motivation, self-regulation, and emotional well-being are gaining prominence, supported by advances in Natural Language Processing (NLP) and sentiment analysis of student-generated content (Zhang & Xu, 2024). Physiological data from wearable devices, though still emerging, offer real-time signals of cognitive readiness and stress, but raise important ethical considerations. Umer et al. (2023) presented a systematic literature review on the use of predictive analytics in higher education to forecast student performance and identify at-risk learners. By analyzing studies from 2008 to 2018, the review highlights how historical data and machine learning techniques have been employed to model learning behaviors and support timely interventions. It also discusses methodological trends, challenges in data interpretation, and outlines future research directions. Ko et al. (2023), Explores how students compensate for learning loss during a pandemic, focusing on the role of artificial intelligence (AI) in this process. It examines how students' use of an AI-powered learning app varies in quantity, pattern, and pace depending on their exposure to pandemic threats and their proximity to academic goals. Findings show that students in the epicenter of a COVID-19 outbreak initially reduce app usage but eventually increase it, use it more consistently, and return to their curriculum pace, indicating compensatory behavior. Additionally, the urgency of approaching academic goals, such as university entrance exams, influences these learning behaviors. The study highlights the potential of AI-driven educational technologies to support both immediate learning and long-term recovery following disruptions (Motz et al., 2023). Critically examines the alignment between the stated goals of learning analytics, understanding and optimizing student learning through learner data, and the actual practices within the field. Analyzing research published in top venues, including the Learning Analytics and Knowledge (LAK) conferences and the *Journal of Learning Analytics* from 2020 to 2022, the authors reveal significant gaps: 37.4% of articles do not use data from real learners, 71.1% fail to measure student learning, and 89.0% do not attempt to intervene in the learning process. These findings highlight a concerning disconnect between the foundational mission of learning analytics and current research trends. The authors call for critical reflection and dialogue within the community to realign the field with its core objectives of evidence-based understanding and improvement of educational outcomes. Ahn et al. (2021), Explores how crowdsourcing can help educators efficiently process everyday educational data, such as student work and paper-based artifacts, into actionable analytics. Through two design experiments involving crowdsourced scoring of open-ended assessments, the researchers address challenges related to crowd expertise and learning. They evaluate design strategies such as screening participants, offering multimedia instruction, and prompting explanations for responses. The findings highlight both the practical potential of crowdsourcing for educational data analysis and its value as a learning opportunity for crowd participants. The study offers important design insights for making educational data more usable for educators through collective intelligence (Carpenter et al., 2021), It investigates the role of reflection in inquiry-driven, game-based learning by examining how middle-school students reflect while interacting with *Crystal Island,* a game-based environment for learning microbiology. Reflection is essential for fostering higher-order thinking and self-regulated learning, yet it presents challenges in terms of how it is measured, modeled, and supported (Waheed et al., 2023a). Using embedded prompts, the researchers elicited written reflections from 105 students and analyzed their relationship to learning outcomes. The results show that specific features of students' reflections and problem-solving behaviors are predictive of reflection depth and correlate with gains in science knowledge and problem-solving skills. The study offers insights for designing adaptive support in game-based learning environments to promote deeper reflection and improved learning outcomes. (Susnjak, 2024), Addresses key limitations in current Learning Analytics research, which has largely emphasized predictive modeling to identify at-risk students while neglecting interpretability and actionable support. It proposes a novel framework that combines transparent machine learning with prescriptive analytics, leveraging the capabilities of eXplainable AI (XAI) and large language models like ChatGPT to provide both interpretable predictions and personalized, human-readable remedial advice. Using a real-world dataset of approximately 7,000 learners from 2018 to 2022, the study demonstrates how predictive models can be effectively integrated with prescriptive tools to not only identify students at risk of non-completion but also guide them with targeted, evidence-based feedback. This work advances the field by bridging the gap between prediction, explanation, and actionable intervention in educational settings. Liang et al. (2024) work tackles the persistent challenge of delivering personalized feedback at scale by enhancing Prescriptive Learning Analytics (PLA) with a novel, learning activity-based feature engineering approach. While PLA combines predictive models with explainable AI (XAI) to provide actionable feedback, not all predictive features translate well into meaningful prescriptions. To bridge this gap, the authors designed features grounded in student learning activities that support both accurate prediction and high-quality feedback generation. Through empirical evaluation in a large university course, PLA-generated feedback was assessed against teacher-written feedback using four criteria: Readily Applicability, Readability, Relational quality, and Specificity. Results showed that PLA-generated feedback maintained strong predictive performance and was rated significantly higher than teacher-written feedback across all criteria. Most instructors also found the feedback applicable and actionable. This work offers a scalable and effective method for generating high-quality, personalized feedback and makes its tools publicly available via GitHub. Crompton & Burke, (2023), analyzed 138 studies on artificial intelligence in higher education (AIEd HE) published between 2016 and 2022, using PRISMA guidelines and a combination of a priori and grounded coding methods. Key findings reveal a sharp increase in publications during 2021 and 2022, signaling growing global interest. The geographic research focus has shifted, with China now surpassing the U.S. in publication volume. Additionally, education departments have become the most dominant source of AIEd research, correcting earlier disciplinary imbalances. Most studies focused on undergraduate students (72%), with language learning (writing, reading, vocabulary) as the most common subject area. AIEd tools were primarily aimed at students (72%), followed by instructors (17%) and administrators (11%). Five primary application areas emerged: assessment/evaluation, prediction, AI assistants, intelligent tutoring systems (ITS), and managing student learning. The review also highlights gaps and opportunities for future research, particularly in exploring new AI tools like ChatGPT. Fahd et al. (2022) presented a comprehensive systematic review and meta-analysis of research on the application of machine learning (ML) in higher education (HE), with a specific focus on predicting student academic performance, identifying at-risk students, and addressing attrition. As ML increasingly transforms educational data analysis, it offers valuable insights into enhancing educational quality and decision-making. Despite its growing use, the literature lacks a consolidated review capturing overarching trends and methodological patterns in this domain. To address this gap, the study adopts the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure methodological rigor in identifying and analyzing relevant studies. Following a structured selection and filtering process, 89 peer-reviewed articles published between 2010 and 2020 were included for in-depth analysis. The review categorizes ML approaches spanning supervised, unsupervised, and reinforcement learning, and examines commonly used algorithms, evaluation metrics, and demographic factors. The results offer quantitative insights into prevailing publication patterns, model effectiveness, and emerging trends, thereby contributing to a clearer understanding of how ML can be effectively leveraged to monitor and improve student outcomes in HE. This work fills a critical gap in the educational technology literature and serves as a foundation for future research and institutional practice in data-driven student support. Valdiviezo-Diaz & Chicaiza, (2024) surveyed recent research (2019–2023) on predicting students' academic performance and dropout rates using machine learning (ML). It reviews studies that applied various ML algorithms across diverse educational settings, utilizing data such as demographics, academic history, and student interactions. The findings show that ML models can predict academic outcomes with high accuracy. However, challenges remain, including the need for effective data collection and preprocessing, as well as addressing ethical concerns related to student data use. The study offers valuable insights for educators, administrators, and researchers aiming to enhance student success through data-driven methods. The integration of machine learning (ML) and deep learning (DL) (Oise & Akpowehbve, 2024), into higher education (HE) has significantly reshaped how institutions understand and enhance student learning. Leveraging diverse data sources such as learning management system logs, academic records, and even sentiment and physiological data, these technologies enable personalized, proactive interventions and timely feedback. Predictive analytics now plays a central role in learning analytics (LA) and educational data mining (EDM), helping to forecast academic performance and identify at-risk students. Recent developments show a shift toward prescriptive analytics, with explainable AI (XAI) methods like SHAP and LIME making model outputs more interpretable and actionable. AI-powered tools such as intelligent tutoring systems and real-time dashboards have been particularly valuable during crises like the COVID-19 pandemic. Global research interest has surged since 2021, especially in areas like language learning, with China emerging as a leading contributor.

Despite these advances, significant challenges remain. Many studies rely on synthetic datasets or lack validation in real-world educational contexts, leading to concerns about scalability, reproducibility, and model generalizability. A common issue is the lack of interpretability in ML models (Oise et al., 2025), which limits their practical application for educators. Although interest in multimodal data is growing, including emotional and physiological indicators, ethical and technical challenges hinder widespread adoption. There is a need for more real-time, context-aware analytics systems that combine cognitive, behavioral, and emotional signals to better understand learner engagement. Future research must focus on explainable, ethical, and inclusive ML systems that align with educational goals and regulatory standards like GDPR and FERPA. Longitudinal studies and human-in-the-loop systems are also essential for assessing long-term impact and ensuring interventions are meaningful, equitable, and supportive of all students. In this study, we explore the use of learning analytics to predict student outcomes using the Open University Learning Analytics Dataset (OULAD). By analyzing behavioral and temporal features, especially VLE click activity, we achieved a classification accuracy of 71% and ROC-AUC of 0.79. Using SHAP values for model interpretability, the findings emphasize the predictive value of engagement metrics over demographic attributes, highlighting the potential of transparent and ethical AI to inform early intervention strategies in higher education.

MATERIALS AND METHODS

The paper employs a standard predictive modeling pipeline using the Open University Learning Analytics Dataset (OULAD) to forecast student success. After integrating multiple data tables (demographics, assessments, and VLE logs), the authors engineered behavioural and demographic features, focusing particularly on student engagement metrics like total click counts. The task was framed as a binary classification predicting whether a student would pass or fail/withdraw from a course.

Data collection & integration

The dataset originates from the Open University, the UK's largest academic institution, with 2 million students since its founding in 1969, primarily serving off-campus learners. It captures data from the university's Virtual Learning Environment (VLE), used for course access, discussions, assessments, and grade tracking. The dataset covers seven selected courses (called modules), across different semesters (denoted by "B" for the second semester and "J" for the first). It includes student demographics (e.g., age, gender, location, education level, disability status), assessment scores, and detailed interactions with the VLE.

Feature engineering & cleaning

Behavioral aggregates were derived from the VLE data, most notably total-clicks, which summed up all interactions by each learner. The authors also retained categorical demographic variables like gender and age-band, which were label-encoded. Missing values were handled through simple imputation, and notably, no records were excluded from the dataset. SHAP analysis later confirmed that these engineered features contributed meaningfully to the model.

Problem formulation

The predictive task was defined as a binary classification problem, distinguishing between students who completed a module (Pass or Distinction) and those who did not (Fail or Withdraw). The positive class, coded as 1, represented successful outcomes. This formulation was consistently reflected in the confusion matrix and related analysis.

Model training

While the paper does not specify the exact algorithm used for classification, it is clear that a single binary classifier was trained. The dataset was split into training and testing sets, with the test set containing 6,519 instances. The model was tuned using metrics such as balanced accuracy and F-measure, though no details about cross-validation procedures were provided.

RESULTS AND DISCUSSION

The predictive model developed in this study was evaluated using a comprehensive set of classification metrics on a test set comprising 6,519 student enrollments. The binary classification task aimed to predict whether a student would complete a course with a pass or distinction versus a failure or withdrawal. The model achieved an overall classification accuracy of 71%, with precision and recall scores of approximately 0.73 and 0.70, respectively. Performance was consistent across both classes, with balanced F1 scores, indicating the model's robustness in handling imbalanced outcomes. Additionally, the ROC-AUC score of 0.79 reflected strong discriminative capability in distinguishing between successful and at-risk students. A detailed confusion matrix revealed 1,873 misclassified instances: 918 false negatives (students predicted to fail but who passed) and 955 false positives (students predicted to pass but who ultimately failed or withdrew). These misclassification rates highlight important trade-offs in real-world educational settings: false negatives may result in missed opportunities for timely interventions, while false positives could lead to unnecessary allocation of resources toward students who may not require additional support. Hence, achieving a balance between sensitivity and specificity is crucial for effective deployment. For model interpretability, SHAP (SHapley Additive exPlanations) was employed to provide transparency into feature contributions. The analysis confirmed that *total_clicks* a measure of students' engagement with the virtual learning environment (VLE) was the most influential predictor. Conversely, protected demographic attributes such as *gender* and *age_band* showed minimal impact on the model's output, suggesting a lower risk of demographic bias and reinforcing the model's emphasis on behavior-based predictors. Ethical and practical considerations were integral to the study. The authors underscored the importance of transparency, privacy, and fairness in predictive analytics. They advocated for the use of explainable AI (XAI) tools, such as visual dashboards, to support academic staff in making informed and ethical intervention decisions. These considerations shaped not only the technical aspects of model development but also the proposed application frameworks, ensuring that predictive insights are actionable, interpretable, and ethically grounded.

Table 1: Classification Report

	Precision	Recall	F1-Score	Support
0	0.73	0.73	0.73	3442
1	0.70	0.69	0.69	3077
Accuracy			0.71	6519
Macro Avg	0.71	0.71	0.71	6519
Weighted Avg	0.71	0.71	0.71	6519

Table 1 depicts the classification report shows the performance of a binary classification model using precision, recall, F1-score, and support. For class 0, the model achieved a precision, recall, and F1-score of 0.73, while for class 1, these metrics were slightly lower at 0.70, 0.69, and 0.69, respectively. The support values indicate a relatively balanced dataset, with 3442 samples for class 0 and 3077 for class 1. The overall accuracy of the model is 71%, meaning it correctly classified 71% of all test instances. Both the macro and weighted averages for precision, recall, and F1-score are also 0.71, suggesting consistent performance across both classes. Although the model performs reasonably well, there is a slight performance drop in predicting class 1, highlighting potential areas for further improvement, especially if class 1 represents a critical category in the application context.

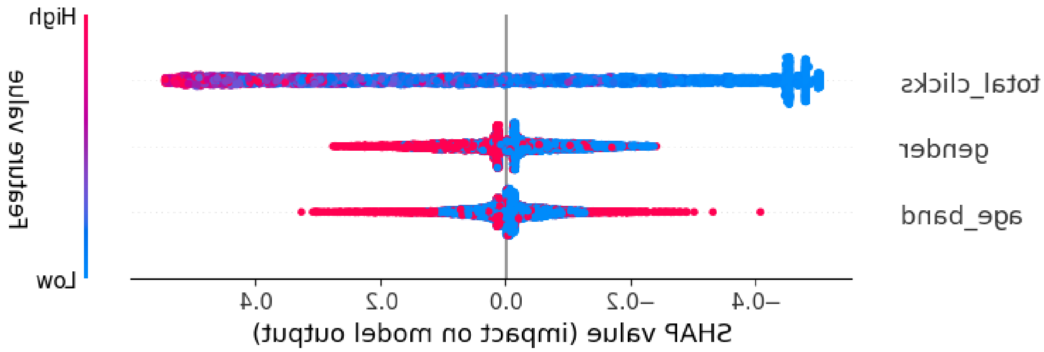

Figure 1: Shap Value

Figure 1 depicts a SHAP summary plot illustrating the impact of three features: total_clicks, gender, and age_band, on a model's predictions. The x-axis represents the SHAP value, indicating how much each feature contributes to pushing the prediction away from the average (either positively or negatively). Each dot corresponds to a single instance and is colored by the feature value (red for high, blue for low). The total_clicks feature has the most significant influence on the model output, as demonstrated by its wide range of SHAP values; higher values (in red) tend to increase the prediction, while lower values (in blue) pull it down. The features gender and age_band show less influence, with SHAP values clustered closer to zero, indicating a smaller effect on the model's decisions. Overall, the plot highlights total_clicks as the most important predictor, while gender and age_band contribute minimally.

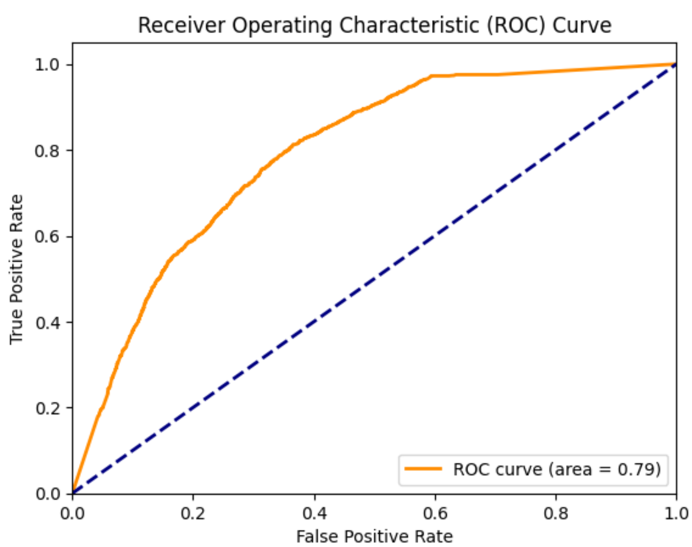

Figure 2: ROC (Receiver Operating Characteristic) curve

Table 2 depicts the ROC (Receiver Operating Characteristic) curve illustrates the performance of a binary classification model across various threshold settings. The x-axis shows the false positive rate (FPR), while the y-axis shows the true positive rate (TPR) or sensitivity. The solid orange line represents the model's performance, and the diagonal dashed line indicates a random classifier (with no discriminative power). The area under the ROC curve (AUC) is 0.79, indicating that the model has good discriminative ability, substantially better than random guessing. AUC values closer to 1.0 suggest excellent performance, while values near 0.5 suggest poor performance. Overall, this ROC curve confirms that the model is fairly effective at distinguishing between the two classes.

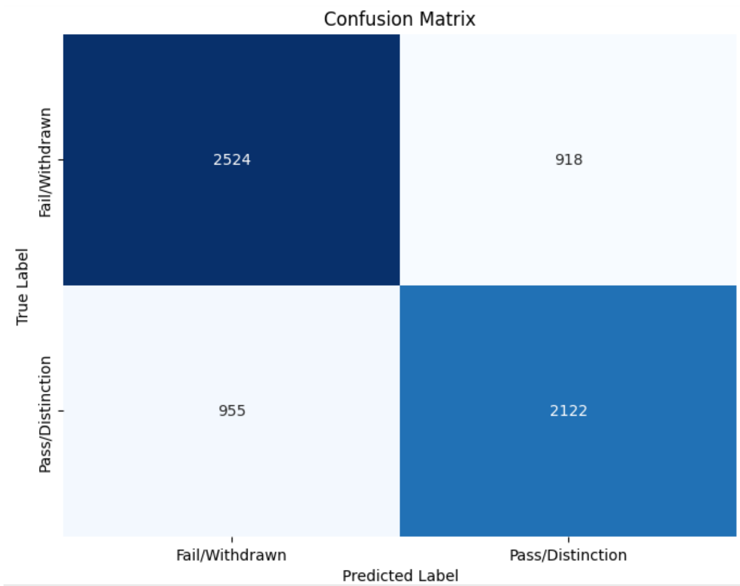

Figure 3: Confusion matrix

Table 3 depicts, confusion matrix that shows the model correctly predicted 2,524 students as Fail/Withdraw and 2,122 as Pass/Distinction, while misclassifying 918 students who failed/withdrew as passing and 955 students who passed as failing. Out of 6,519 total predictions, 4,646 were accurate, reflecting a moderately strong classification performance. Although the model performs reasonably well, the notable number of false positives and false negatives suggests room for improvement in both sensitivity and specificity. These results are consistent with the earlier reported accuracy of 71% and an ROC AUC of 0.79, indicating a fair but improvable ability to distinguish between the two academic outcomes.

The findings of this study reaffirm the centrality of student engagement data, particularly granular behavioural metrics such as total VLE click activity, as powerful predictors of academic outcomes. This aligns with a well-established trend in the learning analytics literature, which underscores the diagnostic value of digital trace data in forecasting learner performance. Notably, the incorporation of temporally aggregated engagement features strengthens predictive accuracy by capturing nuanced, time-dependent patterns in study behaviour, which static metrics alone may overlook. This temporal dimension enhances the model's ability to discern early warning signals embedded in learners' longitudinal interaction profiles, thereby contributing to more timely and targeted interventions. However, the model's predictive efficacy must be critically evaluated in light of its moderate false-positive and false-negative rates, which pose substantive implications for real-world educational deployment. False negatives, where at-risk students are not flagged, can result in missed opportunities for support, potentially exacerbating dropout risk. Conversely, false positives may lead to the misallocation of institutional resources and the imposition of unnecessary support on students who would have succeeded independently. These outcomes underscore the need to strike a careful balance between sensitivity and specificity, especially when predictive models inform automated or semi-automated decision-making processes that impact student trajectories.

A particularly commendable aspect of the study is its emphasis on model interpretability through SHAP (SHapley Additive Explanations). By quantifying the contribution of each feature to individual predictions, SHAP not only enhances transparency but also fosters trust among key stakeholders, including educators, academic advisors, and learners. The results show that total_clicks dominate the predictive landscape, while protected attributes such as gender and age_band exhibit minimal influence. This observation tentatively suggests a reduced risk of algorithmic bias; however, without formal fairness metrics or bias audits, such conclusions remain preliminary. Future work must adopt rigorous fairness evaluation frameworks to assess differential predictive performance across demographic subgroups.

Despite its strengths, the study exhibits notable methodological limitations that constrain its reproducibility and generalizability. Chief among these is the lack of disclosure regarding the specific classification algorithm employed, as well as the absence of detail on cross-validation, hyperparameter tuning, and model selection criteria. These omissions limit both the robustness of the reported results and the ability of other researchers to replicate or extend the work. Addressing these gaps is critical for advancing reproducible science in the learning analytics domain. In addition, the exploration of more sophisticated modeling approaches, such as ensemble methods, recurrent neural networks (RNNs), or transformer-based architectures, may yield enhanced performance, particularly when dealing with sequential data or multimodal feature sets (G. P. Oise & Konyeha, 2024). From an applied perspective, the findings have direct relevance to the design and deployment of early warning systems (EWS) and Learning Analytics Dashboards (LADs). Instructor-facing LADs can assist educators in identifying struggling students early, while student-facing dashboards can promote self-regulated learning by providing real-time feedback on engagement and progress (Onyema et al., 2022). However, despite their growing popularity, many existing tools fall short of delivering prescriptive analytics, offering insights into what is happening, but not why or how to act on it. Moreover, few have been validated in controlled environments or assessed for long-term impact on learner success and institutional outcomes.

Existing EWS platforms such as Othot AI and the S3 Framework provide practical illustrations of analytics-driven interventions. By integrating academic, behavioural, and even financial data, these systems have demonstrated tangible benefits such as 5–12% increases in retention rates during pilot phases, highlighting the transformative potential of data-informed support strategies. Likewise, analytics-based strategic planning can optimize resource allocation for advising, mental health services, and curricular improvements, while identifying systemic bottlenecks and underperforming learner cohorts (Rashidian & Hilal, 2022). Nevertheless, the institutionalization of learning analytics presents a series of ethical, legal, and operational challenges. Ensuring compliance with data protection regulations such as the General Data Protection Regulation (GDPR) and the Family Educational Rights and Privacy Act (FERPA) is imperative, particularly as analytics systems handle sensitive personal data (Sassirekha & Vijayalakshmi, 2022). Moreover, the use of black-box models exacerbates transparency issues, complicating efforts to build stakeholder trust. Additional barriers include technical limitations, interoperability issues, and varying levels of digital literacy among faculty and support staff all of which hinder widespread adoption. Looking ahead, the evolution of learning analytics will likely be shaped by advances in explainable artificial intelligence (XAI), with techniques such as SHAP and LIME playing pivotal roles in bridging the gap between accuracy and interpretability. Emerging innovations in multimodal, real-time analytics involving data streams from IoT devices, wearables, and mobile apps hold promise for offering a holistic view of student engagement, motivation, and well-being. However, for these approaches to be impactful at scale, greater attention must be paid to issues of scalability, equity, and generalizability across diverse institutional contexts. Finally, there is a critical need for longitudinal research to assess the sustained effects of analytics-driven interventions not only on academic performance but also on learners' personal development, mental health, and post-graduate outcomes. The current study contributes to this growing body of work by offering an interpretable and ethically conscious predictive framework that balances performance with transparency, paving the way for responsible, evidence-based educational innovation.

Table 2: Comparative Analysis of Predictive Learning Analytics Studies

Study	Dataset / Focus	Accuracy	Key Predictors	Key Contribution
Our Study (2025)	OULAD (Open University Learning Analytics Dataset)	71%	Total VLE clicks, engagement, and temporal patterns	Transparent, ethical prediction using behavioral data; minimal demographic bias
(Simaei & Rahimifard, 2024)	Meta-analysis of 89 studies in higher education	60%	Academic records, LMS interaction data	Overview of ML performance, methods, and metrics across a decade of research
(Waheed et al., 2023b)	Self-paced education with neural networks	85%	Formative assessments, click behavior	Early identification of at-risk learners
(Albreiki et al., 2022)	Framework for remedial suggestions using explainable ML	78%	LMS activity, logins, and resource views	Rule-driven intervention support for struggling students
(Capuano et al., 2023b)	Online course environments (MOOCs)	83%	Course access patterns, engagement	Interpretable predictors in massive online courses

Table 2 depicts the comparative analysis shows that while the predictive model in this study achieved a modest accuracy of 71%, it stands out because of its focus on transparency, ethical AI, and the use of SHAP for model interpretability. Compared to other studies, such as Waheed et al. (2023b) and Capuano et al. (2023b), which reported higher accuracies of 85% and 83% respectively, this study emphasizes reducing demographic bias and supporting explainable decision-making. Albreiki et al. (2022) also discussed interpretability but favored rule-based interventions, while Simaei & Rahimifard's (2024) meta-analysis confirmed that most models in educational prediction range from 60% to 95% accuracy, depending on the methodology. Overall, this study aligns with current trends that favor interpretable and ethically conscious learning analytics, even though there is still room for improvement in model performance.

CONCLUSION

This study shows how student engagement data, especially Virtual Learning Environment click activity, can predict academic success using a transparent and interpretable machine learning model. With 71% accuracy and an ROC-AUC of 0.79, the model emphasizes the strong predictive power of behavioral metrics while reducing dependence on sensitive demographic information. The use of SHAP values improves transparency, promoting ethical and fair decision-making. However, the lack of methodological details such as the algorithm type and validation procedures limits reproducibility. Despite moderate misclassification rates, the results support developing early warning systems and learning analytics tools that can guide timely interventions. Future research should address current limitations, implement rigorous evaluation methods, and explore scalable, ethical solutions in various educational settings.

REFERENCES

Afzaal, M., Nouri, J., Zia, A., Papapetrou, P., Fors, U., Wu, Y., Li, X., & Weegar, R. (2021). Generation ofAutomatic Data-Driven Feedback to Students Using Explainable Machine Learning. In I. Roll, D. McNamara, S. Sosnovsky, R. Luckin, & V. Dimitrova (Eds.), *Artificial Intelligence in Education* (Vol. 12749, pp. 37–42). Springer International Publishing. https://doi.org/10.1007/978-3-030-78270-2_6

Ahn, J., Nguyen, H., Campos, F., & Young, W. (2021). Transforming Everyday Information into Practical Analytics with Crowdsourced Assessment Tasks. *LAK21: 11th International Learning Analytics and Knowledge Conference*, 66–76. https://doi.org/10.1145/3448139.3448146

Albreiki, B., Habuza, T., & Zaki, N. (2022). Framework for automatically suggesting remedial actions to help students at risk based on explainable ML and rule-based models. *International Journal of Educational Technology in Higher Education*, *19*(1), 49. https://doi.org/10.1186/s41239-022-00354-6

Capuano, N., Rossi, D., Ströele, V., & Caballé, S. (2023a). Explainable Prediction of Student Performance in Online Courses. In D. Guralnick, M. E. Auer, & A. Poce (Eds.), *Creative Approaches to Technology-Enhanced Learning for the Workplace and Higher Education* (Vol. 767, pp. 639–652). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-41637-8_52

Capuano, N., Rossi, D., Ströele, V., & Caballé, S. (2023b). Explainable Prediction of Student Performance in Online Courses. In D. Guralnick, M. E. Auer, & A. Poce (Eds.), *Creative Approaches to Technology-Enhanced Learning for the Workplace and Higher Education* (Vol. 767, pp. 639–652). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-41637-8_52

Carpenter, D., Cloude, E., Rowe, J., Azevedo, R., & Lester, J. (2021). Investigating Student Reflection during Game-Based Learning in Middle Grades Science. *LAK21: 11th International Learning Analytics and Knowledge Conference*, 280–291. https://doi.org/10.1145/3448139.3448166

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, *20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Fahd, K., Venkatraman, S., Miah, S. J., & Ahmed, K. (2022). Application of machine learning in higher education to assess student academic performance, at-risk, and attrition: A meta-analysis of literature. *Education and Information Technologies*, *27*(3), 3743–3775. https://doi.org/10.1007/s10639-021-10741-7

Hwang, G.-J., & Tu, Y.-F. (2021). Roles and Research Trends of Artificial Intelligence in Mathematics Education: A Bibliometric Mapping Analysis and Systematic Review. *Mathematics*, *9*(6), 584. https://doi.org/10.3390/math9060584

James, G. G., P, O. G., G, C. E., A, M. N., F, E. W., & E, O. P. (2024). Optimizing Business Intelligence System Using Big Data and Machine Learning. *Journal of Information Systems and Informatics*, 6(2), 1215–1236. https://doi.org/10.51519/journalisi.v6i2.631

Ko, G. Y., Shin, D., Auh, S., Lee, Y., & Han, S. P. (2023). Learning Outside the Classroom During a Pandemic: Evidence from an Artificial Intelligence-Based Education App. *Management Science*, *69*(6), 3616–3649. https://doi.org/10.1287/mnsc.2022.4531

Liang, Z., Sha, L., Tsai, Y.-S., Gašević, D., & Chen, G. (2024). Towards the Automated Generation of Readily Applicable Personalised Feedback in Education. In A. M. Olney, I.-A. Chounta, Z. Liu, O. C. Santos, & I. I. Bittencourt (Eds.), *Artificial Intelligence in Education* (Vol. 14830, pp. 75–88). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-64299-9_6

Motz, B. A., Bergner, Y., Brooks, C. A., Gladden, A., Gray, G., Lang, C., Li, W., Marmolejo-Ramos, F., & Quick, J. D. (2023). LAK of Direction: Misalignment Between the Goals of Learning Analytics and its Research Scholarship. *Journal of Learning Analytics*, 1–13. https://doi.org/10.18608/jla.2023.7913

Oise, G., & Konyeha, S. (2024). E-WASTE MANAGEMENT THROUGH DEEP LEARNING: A SEQUENTIAL NEURAL NETWORK APPROACH. *FUDMA JOURNAL OF SCIENCES*, *8*(3), 17–24. https://doi.org/10.33003/fjs-2024-0804-2579

Oise, G. P., & Akpowehbve, O. J. (2024). Systematic Literature Review on Machine Learning Deep Learning and IOT-based Model for E-Waste Management. *International Transactions on Electrical Engineering and Computer Science*, *3*(3), 154–162. https://doi.org/10.62760/iteecs.3.3.2024.94

Oise, G. P., & Konyeha, S. (2024). Deep Learning System for E-Waste Management. *The 3rd International Electronic Conference on Processes*, 66. https://doi.org/10.3390/engproc2024067066

Oise, G. P., Nwabuokei, O. C., Akpowehbve, O. J., Eyitemi, B. A., & Unuigbokhai, N. B. (2025). TOWARDS SMARTER CYBER DEFENSE: LEVERAGING DEEP LEARNING FOR THREAT IDENTIFICATION AND PREVENTION. *FUDMA JOURNAL OF SCIENCES*, *9*(3), 122–128. https://doi.org/10.33003/fjs-2025-0903-3264

Onyema, E. M., Almuzaini, K. K., Onu, F. U., Verma, D., Gregory, U. S., Puttaramaiah, M., & Afriyie, R. K. (2022). Prospects and Challenges of Using Machine Learning for Academic Forecasting. *Computational Intelligence and Neuroscience*, *2022*, 1–7. https://doi.org/10.1155/2022/5624475

Rashidian, N., & Hilal, M. A. (2022). Applications of machine learning in surgery: Ethical considerations. *Artificial Intelligence Surgery*. https://doi.org/10.20517/ais.2021.13

Sassirekha, M. S., & Vijayalakshmi, S. (2022). Predicting the academic progression in student's standpoint using machine learning. *Automatika*, *63*(4), 605–617. https://doi.org/10.1080/00051144.2022.2060652

Simaei, E., & Rahimifard, S. (2024). AI-based decision support system for enhancing end-of-life value recovery from e-wastes. *International Journal of Sustainable Engineering*, *17*(1), 1–17. https://doi.org/10.1080/19397038.2024.2306293

Susnjak, T. (2024). Beyond Predictive Learning Analytics Modelling and onto Explainable Artificial Intelligence with Prescriptive Analytics and ChatGPT. *International Journal of Artificial Intelligence in Education*, *34*(2), 452–482. https://doi.org/10.1007/s40593-023-00336-3

Umer, R., Susnjak, T., Mathrani, A., & Suriadi, L. (2023). Current stance on predictive analytics in higher education: Opportunities, challenges and future directions. *Interactive Learning Environments*, *31*(6), 3503–3528. https://doi.org/10.1080/10494820.2021.1933542

Valdiviezo-Diaz, P., & Chicaiza, J. (2024). Prediction of Academic Outcomes Using Machine Learning Techniques: A Survey of Findings on Higher Education. In M. Botto-Tobar, M. Zambrano Vizuete, S. Montes León, P. Torres-Carrión, & B. Durakovic (Eds.), *International Conference on Applied Technologies* (Vol. 2049, pp. 206–218). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-58956-0_16

Waheed, H., Hassan, S.-U., Nawaz, R., Aljohani, N. R., Chen, G., & Gasevic, D. (2023a). Early prediction of learners at risk in self-paced education: A neural network approach. *Expert Systems with Applications*, *213*, 118868. https://doi.org/10.1016/j.eswa.2022.118868

Waheed, H., Hassan, S.-U., Nawaz, R., Aljohani, N. R., Chen, G., & Gasevic, D. (2023b). Early prediction of learners at risk in self-paced education: A neural network approach. *Expert Systems with Applications*, *213*, 118868. https://doi.org/10.1016/j.eswa.2022.118868

Zhang, Z., & Xu, L. (2024). Student engagement with automated feedback on academic writing: A study on Uyghur ethnic minority students in China. *Journal of Multilingual and Multicultural Development*, *45*(8), 3466–3479. https://doi.org/10.1080/01434632.2022.2102175