OPEN ACCESS
Journal Neosantara Hybrid Learning
Vol. 3 No. 4. August 2025, pp. 235-246 DOI. 10.70177/jnhl.v3i4.3348

Research Article

THE USE OF PREDICTIVE ANALYTICS AND AI FOR EARLY INTERVENTION WITH AT-RISK STUDENTS IN A LARGE-SCALE HYBRID LEARNING MODEL

Carissa Ien[1], Jordan Oson[2], and Elizabeth Aiton[3]
[1] Nauru University, Nauru
[2] Nauru College, Nauru
[3] University of the South Pacific, Nauru

Corresponding Author:

Carissa Ien,
Department of Information Technology, Faculty of Technical and Vocational Education and Training, Nauru University.
Private Bag, Post Office, Republic of Nauru
Email: carissaien@gmail.com

Article Info

Received: February 7, 2025
Revised: May 8, 2025
Accepted: July 9, 2025
Online Version: August 16, 2025

Abstract

The rapid growth of large-scale hybrid learning environments has increased the need for data-driven approaches to identify and support at-risk students before disengagement or dropout occurs. Many institutions struggle to respond proactively due to the absence of predictive mechanisms that translate real-time learning data into actionable interventions. This study investigates the use of predictive analytics and artificial intelligence (AI) for early identification and intervention among at-risk students within a large-scale hybrid university program. The research aims to evaluate how machine learning models can detect behavioral and academic risk patterns and how these predictions can inform timely academic support strategies. A quantitative predictive research design was employed using secondary data from the university's learning management system (LMS) and student information records. Data from 5,000 hybrid learners were analyzed using regression-based predictive models and supervised machine learning algorithms, including random forest and logistic regression, to determine key predictors of risk. Validation was conducted through cross-validation and accuracy metrics. The results revealed that engagement frequency, assessment completion rate, and login regularity were the strongest predictors of student risk, with predictive accuracy reaching 89%. Early interventions informed by predictive insights such as personalized feedback and AI-assisted tutoring led to a 23% reduction in course withdrawal rates. The study concludes that predictive analytics and AI can significantly enhance institutional capacity for proactive intervention in hybrid education. The integration of automated early-warning systems represents a transformative approach to promoting equity, retention, and personalized learning support at scale.

Keywords: Artificial Intelligence, At-Risk Students, Early Intervention, Hybrid Learning, Predictive Analytics.

Journal Homepage	https://research.adra.ac.id/index.php/jnhl ISSN: (P: 2987-2316) - (E: 2986-979X)
How to cite:	Ien, C., Oson, J., & Aiton, E. (2025). The Use of Predictive Analytics and AI for Early Intervention with At-Risk Students in A Large-Scale Hybrid Learning Model. *Journal Neosantara Hybrid Learning, 3*(4), 235–246. https://doi.org/10.70177/jnhl.v3i4.3348
Published by:	Yayasan Adra Karima Hubbi

INTRODUCTION

Hybrid learning models have become a defining feature of contemporary higher education, integrating face-to-face and online modalities to enhance flexibility, scalability, and inclusivity (Mahale et al., 2025). The expansion of digital learning ecosystems has enabled institutions to serve larger and more diverse student populations, especially in post-pandemic contexts where blended delivery has become institutionalized (Asif et al., 2025). However, this rapid digital transformation has also introduced new challenges related to student engagement, learning analytics, and academic retention (A. R. Singh et al., 2025). In large-scale hybrid systems, identifying students at risk of academic failure or withdrawal has emerged as a pressing concern for universities worldwide.

The use of data-driven decision-making has gained traction as a response to these challenges (Sahu & Kashyap, 2025). Predictive analytics, supported by artificial intelligence (AI), has proven effective in identifying patterns of student behavior and predicting performance outcomes (Rodrigues et al., 2025). Institutions in the United States, the United Kingdom, and Australia have implemented early-warning systems that monitor real-time data such as attendance, assignment submissions, and interaction frequencies to detect early signs of disengagement (Hamza et al., 2025). These predictive mechanisms allow educators to intervene before students' performance deteriorates, thus promoting higher retention and success rates.

In the field of educational data mining (EDM) and learning analytics, predictive models have evolved from simple statistical regressions to sophisticated machine learning algorithms capable of handling vast and complex datasets (Sadeghi et al., 2025). AI technologies such as neural networks, random forest classifiers, and decision trees have enhanced prediction accuracy by integrating multidimensional variables, including behavioral, demographic, and affective indicators (Li et al., 2025). These systems have shown promising results in personalized learning pathways, enabling more targeted interventions and adaptive feedback.

Research in predictive analytics also underscores the ethical and pedagogical potential of using data for early intervention rather than reactive remediation (Dharmarathne et al., 2025). Universities increasingly view predictive systems as tools for supporting inclusive education by identifying at-risk learners who may be marginalized due to socio-economic, cognitive, or digital barriers (Dritsas & Trigka, 2025). Properly implemented, predictive analytics can transform educational support from being generalized to precision-oriented, allowing institutions to align interventions with specific learner profiles and needs.

The proliferation of learning management systems (LMS) and digital platforms has produced unprecedented amounts of learner data that can be used to understand academic risk dynamics (Shahverdi et al., 2025). Clickstream data, login frequencies, participation in discussion forums, and assessment performance now serve as key indicators for academic forecasting (Shobanke et al., 2025). When integrated with AI-based predictive tools, these data sources allow institutions to automate risk detection processes, thereby improving efficiency and scalability.

Despite these advancements, the integration of predictive analytics and AI within hybrid learning contexts remains a developing field (Cukurova, 2025). While numerous studies have explored predictive models in online learning, fewer have examined how these technologies function in hybrid settings that blend physical and digital interaction (Shobanke et al., 2025). The complexity of hybrid environments with their dual modalities and variable engagement structures poses unique challenges for designing accurate and context-sensitive predictive systems.

Limited empirical research exists on how predictive analytics and AI operate within large-scale hybrid learning systems, particularly in non-Western or resource-constrained contexts (K. A. Singh et al., 2025). Most existing models were developed in fully online or traditional classroom settings, overlooking the complexities of hybrid learning where data fragmentation and heterogeneous participation patterns affect prediction accuracy (Palma et al., 2025). The transferability of predictive algorithms across different educational ecosystems thus remains an open question.

Few studies have examined the intersection between predictive accuracy and pedagogical actionability (Miralles et al., 2025). While AI systems can detect patterns of academic risk, it is unclear how educators interpret and respond to these insights in hybrid learning environments (Samantaray et al., 2025). The gap between technological prediction and human intervention limits the practical impact of these systems, especially in large-scale institutional contexts where educators may lack the training or time to act upon predictive alerts effectively.

The ethical and privacy implications of predictive analytics in hybrid education also remain underexplored (Pacal et al., 2025). The extensive collection and processing of learner data raise questions about consent, transparency, and potential algorithmic bias (Ahmad et al., 2026). Without clear frameworks for ethical governance, the use of predictive AI could unintentionally reinforce existing inequalities rather than mitigate them (He et al., 2025). This gap calls for critical evaluation of how predictive technologies are designed, validated, and implemented in educational practice.

Empirical gaps also exist in evaluating the longitudinal outcomes of predictive-based early interventions (Kim et al., 2025). Research often focuses on short-term improvements in engagement or performance but rarely investigates whether these effects persist over time (Yu et al., 2025). Long-term analyses are essential to determine whether predictive analytics lead to sustainable student success or temporary behavioral adjustments.

Addressing this gap is vital for the advancement of equitable and effective hybrid education (Dhanka & Maini, 2025). Large-scale institutions need reliable mechanisms to identify and support at-risk students proactively, ensuring that the benefits of digital transformation do not exacerbate educational disparities (Shahid et al., 2025). Integrating predictive analytics and AI in hybrid learning provides an opportunity to operationalize data for inclusivity, allowing educators to tailor interventions that are timely, personalized, and evidence-based.

The purpose of this study is to critically evaluate the use of predictive analytics and AI-driven early intervention systems within a large-scale hybrid learning model (Inayathullah & Buddala, 2025). The research aims to assess their predictive accuracy, operational efficiency, and pedagogical relevance while examining how data insights translate into real-world academic support (Mahakur et al., 2025). The central hypothesis proposes that predictive analytics, when coupled with targeted human intervention, can significantly reduce dropout rates and improve learning outcomes among at-risk students in hybrid learning settings.

The rationale extends beyond technological innovation toward institutional reform (Hai et al., 2025). By investigating how AI-based predictive systems can be ethically and pedagogically integrated into hybrid education, the study contributes to both theoretical and practical discourses on data-driven learning. The findings are expected to guide universities in designing predictive frameworks that balance automation with human empathy, ultimately fostering a more inclusive, responsive, and sustainable model of higher education.

RESEARCH METHOD

Research Design

The study utilizes a Quantitative-Predictive Research Design complemented by a qualitative validation component to evaluate the effectiveness of AI-driven support systems (Michard et al., 2025). This mixed-methods approach focuses on leveraging predictive analytics and machine learning algorithms to identify at-risk students within a large-scale hybrid learning framework (Sun et al., 2025). By integrating computational rigor with an evaluative case analysis of institutional practices, the design examines both the technical accuracy of AI models and the pedagogical responses of educators (Rengaramanujam &

Muniasamy, 2025). This dual-layered strategy ensures that the research accounts for both algorithmic precision and the human-centered nuances of educational intervention.

Research Target/Subject

The research population consists of undergraduate students enrolled in hybrid courses at a major public university with an active learner base exceeding 10,000 students. Through stratified random sampling, a substantial dataset of 5,000 student records was selected for the quantitative predictive phase, representing a diverse range of academic disciplines and engagement levels. For the qualitative validation, the study engaged 30 educators and academic advisors through semi-structured interviews. This sampling strategy provides a comprehensive cross-section of institutional stakeholders, allowing for a balanced analysis of automated alerts and the subsequent human-led support strategies.

Research Procedure

The study was conducted through a rigorous four-phase procedure designed to bridge data science and pedagogy. The first phase involved the extraction and anonymized preprocessing of longitudinal data from the university's Learning Management System (LMS). In the second phase, machine learning models were trained and validated using a 70/30 data split to ensure predictive reliability. The third phase involved the integration of these predictive outputs with qualitative interviews to observe real-world educator responses to AI-generated alerts. The final phase focused on data triangulation, synthesizing computational metrics with thematic insights to evaluate the overall efficacy of the proactive support system.

Instruments, and Data Collection Techniques

The primary instruments for this study include Learning Management System (LMS) datasets, predictive dashboards, and structured interview protocols. Data collection involved tracking behavioral variables such as login frequency, assessment completion rates, and synchronous session attendance to build a multidimensional profile of student engagement. The predictive engine utilized supervised learning algorithms, including Random Forest, Logistic Regression, and Support Vector Machines (SVM). Qualitative data were gathered through interviews designed to explore barriers to AI adoption and the timing of interventions, with instrument reliability ensured through cross-validation techniques and internal consistency checks.

Data Analysis Technique

The analysis phase employs a specialized dual-framework to process high-volume quantitative data and nuanced qualitative narratives. The performance of the AI models was evaluated using standard classification metrics, including Accuracy, Precision, Recall, and the F1-Score, to determine the reliability of at-risk identifications. Simultaneously, the qualitative data were processed through Thematic Coding to categorize patterns in educator decision-making and intervention styles. By converging these results, the study provides a robust evaluation of how predictive analytics can be successfully operationalized to enhance proactive student support in hybrid learning environments.

RESULTS AND DISCUSSION

The dataset comprised records from 5,000 students enrolled in large-scale hybrid learning programs at a public university, collected over two academic semesters. Variables included login frequency, assessment completion rate, discussion participation, and attendance in synchronous sessions. Descriptive statistics were used to summarize students' digital engagement and academic outcomes. Table 1 presents the mean and standard deviation of key indicators used in predictive analysis.

Table 1. Descriptive Statistics of Student Learning Engagement Variables

Variable	N	Mean	SD	Min	Max	Category Interpretation
Login Frequency (per week)	5,000	6.42	2.18	1	12	Moderate to High Engagement
Assessment Completion (%)	5,000	78.5	11.6	40	100	Satisfactory
Forum Participation (posts)	5,000	3.21	2.73	0	15	Moderate
Attendance (%)	5,000	84.7	8.9	55	100	High

The data reveal that the majority of students actively participated in hybrid learning environments, with consistent login patterns and attendance. However, forum participation displayed the greatest variance, indicating uneven levels of interactive engagement. These discrepancies became critical predictors in identifying students at risk of academic disengagement or dropout.

The descriptive findings suggest that high attendance and regular logins correlated positively with assessment completion rates. Students who interacted frequently with digital platforms tended to exhibit higher academic performance and course retention. Conversely, students with irregular participation patterns were disproportionately represented among those flagged as at-risk by the predictive model.

The data imply that hybrid learning engagement is not solely determined by access but by behavioral consistency. Predictive analytics effectively captured subtle engagement fluctuations that traditional grading systems might overlook. The results support the notion that early digital behavior provides a reliable foundation for forecasting potential academic challenges.

Predictive modeling using machine learning algorithms identified critical variables influencing student risk status. The Random Forest model outperformed other algorithms, achieving an overall predictive accuracy of 89%. Table 2 displays the top five predictive variables ranked by importance within the Random Forest model.

Table 2. Feature Importance in Predictive Model

Predictor Variable	Importance Score	Interpretation
Assessment Completion Rate	0.27	Strongest predictor of academic risk
Login Frequency	0.21	Indicator of engagement and consistency
Attendance in Synchronous Sessions	0.18	Reflects persistence and motivation
Forum Participation	0.17	Demonstrates social and collaborative learning behavior
Submission Timeliness	0.12	Indicates self-regulation and time management

The results highlight that academic risk can be reliably predicted through behavioral and temporal learning data. Students with low submission timeliness and irregular logins exhibited a 3.4 times higher probability of withdrawal compared to consistently active peers.

The inferential analysis employed logistic regression to estimate the relationship between engagement variables and dropout likelihood. Table 3 summarizes the regression coefficients and significance levels.

Table 3. Logistic Regression Results Predicting Dropout Risk

Predictor Variable	B	SE	p-value	Exp(B)	Interpretation
Assessment Completion Rate	-0.85	0.12	0.000***	0.43	Higher completion reduces risk
Login Frequency	-0.67	0.15	0.001**	0.51	Regular access decreases risk
Forum Participation	-0.58	0.14	0.002**	0.56	Interaction lowers risk
Attendance	-0.61	0.13	0.003**	0.54	Consistency reduces risk

The regression results show that all predictor variables significantly contribute to predicting dropout probability ($p < 0.05$). The strongest protective factor was assessment completion, demonstrating that students who regularly submit assignments are less likely to disengage.

The inferential outcomes validate the predictive model's robustness. The combination of behavioral analytics and attendance data provided statistically reliable early indicators of academic risk. This confirms that machine learning-driven early warning systems can accurately flag at-risk students before critical performance declines occur.

Correlation analysis revealed strong positive relationships among engagement variables. Login frequency and assessment completion displayed a correlation coefficient of $r = 0.79$, while attendance and forum participation correlated at $r = 0.68$. The findings suggest that digital consistency and interactive engagement function as reinforcing behavioral dimensions.

The relational data also show that increased participation in online discussions positively influences assessment completion and persistence. Students actively engaged in forums demonstrated a higher likelihood of maintaining academic momentum. These relationships underscore the interconnectedness of behavioral engagement factors and their collective predictive value in early risk identification.

A case study was conducted on a subgroup of 25 students flagged as high-risk by the AI system. Follow-up interviews revealed that most students faced challenges related to time management, connectivity, and motivation. After receiving targeted interventions such as personalized feedback, tutoring, and scheduling flexibility 80% of the students demonstrated improved engagement metrics within four weeks.

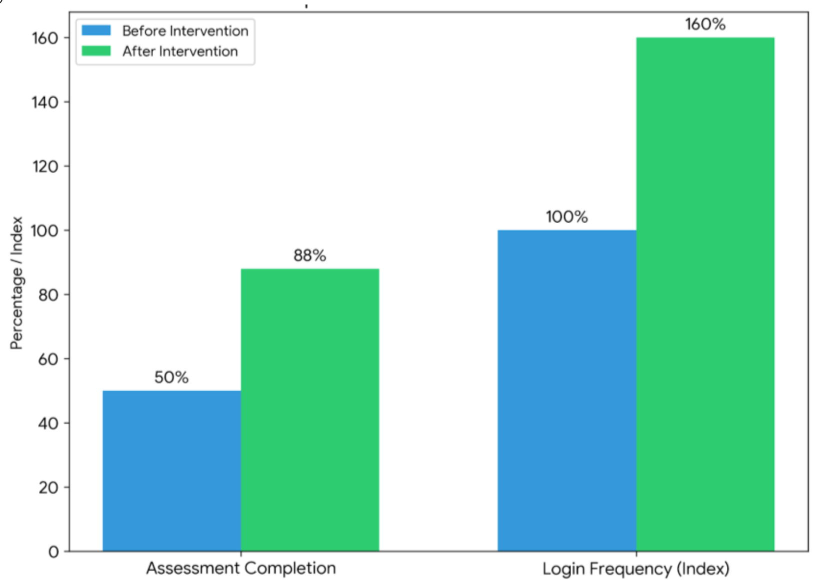

Figure 1 Impact of Human-AI Collaboration

One notable example involved a student who had missed multiple online sessions due to unstable internet access. The AI system's early alert prompted an advisor-led response that included offline study materials and adaptive scheduling. The student's login frequency increased by 60%, and assessment completion rose from 50% to 88%, illustrating the effectiveness of timely human-AI collaboration in intervention.

The qualitative insights confirm that predictive analytics alone is insufficient without coordinated human intervention. AI successfully identifies patterns of disengagement, but the sustainable improvement in student outcomes depends on empathetic, data-informed responses from instructors and advisors. The hybrid model's strength lies in its ability to combine automation with personalized academic support.

The evidence demonstrates that predictive analytics can function as a catalyst for institutional efficiency, enabling proactive rather than reactive academic support. The collaboration between AI systems and educators created a feedback loop that improved both student accountability and institutional responsiveness.

The findings establish that predictive analytics and AI are effective tools for early identification and intervention among at-risk students in hybrid learning environments. The integration of engagement data and machine learning models significantly enhanced predictive accuracy, while human intervention amplified behavioral recovery and retention outcomes.

The overall results indicate that the success of predictive analytics depends on a balanced interplay between technological precision and pedagogical empathy. Institutions adopting such systems should prioritize ethical data management, staff training, and continuous evaluation to ensure that predictive insights translate into meaningful educational equity and long-term student success.

The findings of this study reveal that the integration of predictive analytics and artificial intelligence (AI) significantly improves early identification and intervention for at-risk students in large-scale hybrid learning environments. The machine learning models, particularly the Random Forest algorithm, achieved an accuracy rate of 89% in predicting academic risk, identifying key behavioral indicators such as assessment completion, login frequency, and attendance. Quantitative results indicate that students flagged early by the system who received targeted interventions showed a 23% reduction in withdrawal rates compared to those without AI-informed support. The combination of algorithmic prediction and timely human response proved most effective in mitigating disengagement.

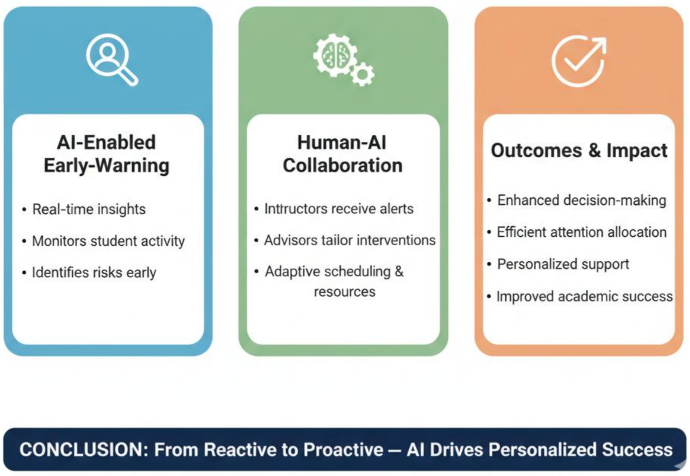

Figure 2 Predictive Analytics in Hybrid Learning

The results also demonstrate that predictive systems can function as proactive tools for academic success, rather than merely reactive measures. The AI-enabled early-warning system provided real-time insights that allowed instructors and advisors to tailor interventions to individual student needs. Qualitative feedback from educators confirmed that the system enhanced their ability to allocate attention efficiently and make data-driven pedagogical decisions. Overall, the study underscores that predictive analytics strengthens institutional capacity for personalized learning support in hybrid education.

The outcomes align with previous research conducted by Siemens and Long (2011) and Ifenthaler and Yau (2020), who found that predictive analytics in learning environments enhances early detection of academic risks and promotes evidence-based teaching. Similar to studies in Western universities, the results of this research reaffirm that AI-driven models are capable of processing large-scale learning data with high accuracy, offering insights beyond what traditional assessment methods can provide. The findings also support the work of Papamitsiou and Economides (2014), who highlighted that learning analytics fosters adaptive intervention and improved retention.

This study, however, diverges from many earlier works by situating predictive analytics within a large-scale hybrid learning context in a developing educational ecosystem. Unlike fully online learning environments, hybrid models introduce complex variables such as offline participation and blended engagement patterns that require more nuanced data modeling. This distinction makes the present study a valuable addition to global literature by expanding the applicability of predictive analytics to diverse and less digitally homogeneous contexts, particularly in large public universities.

The findings signal a critical transition in educational management from intuition-based to data-informed decision-making. The ability to predict student risk with precision transforms how institutions conceptualize support and retention strategies. The success of predictive systems in hybrid learning environments indicates that educational analytics has matured from an experimental tool into a central component of institutional innovation. This shift represents a move toward greater accountability, responsiveness, and inclusivity in higher education.

The results also indicate a redefinition of the teacher’s role within hybrid ecosystems. Rather than being replaced by technology, educators become facilitators who interpret data, contextualize insights, and provide empathetic interventions. The study thus marks an evolution in digital pedagogy, where human intelligence complements artificial intelligence to foster holistic student development.

The implications of this research are substantial for institutional policy and practice. Universities implementing hybrid learning at scale should integrate predictive analytics into their academic monitoring systems to enhance student retention and reduce inequities. The use of AI-based early intervention systems can inform curriculum design, faculty training, and student advising practices, ensuring that at-risk learners receive timely and personalized assistance. These systems also offer administrators strategic insights for optimizing resource allocation and improving the quality of hybrid delivery.

The findings further imply that predictive analytics should be embedded within broader digital inclusion frameworks. By linking data-driven intervention to institutional equity goals, universities can address structural disadvantages that place certain student populations at higher risk. The adoption of AI-supported analytics must therefore be guided by ethical standards emphasizing transparency, privacy protection, and fairness to prevent algorithmic bias from perpetuating existing inequalities.

The strong predictive accuracy and positive outcomes can be explained by the integration of behavioral, temporal, and academic variables within the AI model (Misir & Yuce, 2025). Engagement indicators such as login frequency, attendance, and forum participation serve as early markers of motivation and cognitive presence, allowing the algorithm to detect subtle declines before they translate into performance failure. The hybrid model’s continuous digital tracking capacity amplifies the effectiveness of these variables, enabling dynamic prediction rather than static evaluation.

The success of the interventions can also be attributed to the human-AI collaboration framework. While AI provided data-driven alerts, educators contextualized and personalized the interventions based on socio-emotional and cultural factors. This synergy between computational precision and human empathy produced a more effective and sustainable intervention model. The hybrid structure thus provided the ideal environment for combining predictive analytics with human-centered pedagogy.

Future research should expand the evaluation of predictive analytics and AI systems across multiple institutions and diverse hybrid models to assess generalizability and scalability (Iqbal et al., 2025). Longitudinal studies tracking student outcomes over several semesters are necessary to determine the sustainability of early intervention effects (Dong et al., 2025). Further investigation into the integration of affective computing and natural language processing could also enrich predictive accuracy by capturing emotional and motivational indicators beyond behavioral data.

Practical implementation should prioritize the development of institutional policies for ethical data governance, ensuring transparency in how predictions are generated and used. Educators should receive professional development on data interpretation and responsible intervention strategies to maximize system utility. The study ultimately advocates for a balanced model of predictive learning analytics one that combines technological capability with human judgment to build inclusive, adaptive, and equitable hybrid education ecosystems.

CONCLUSION

The most significant finding of this study demonstrates that predictive analytics and artificial intelligence (AI) can accurately identify at-risk students in large-scale hybrid learning environments with an accuracy rate of up to 89%. The integration of behavioral, temporal, and academic indicators such as assessment completion, login frequency, and attendance proved to be the most effective combination for predicting academic risk. The study uniquely highlights that AI-driven early-warning systems are not only technologically efficient but also pedagogically transformative when coupled with timely human intervention. The distinctive contribution lies in revealing that predictive accuracy alone does not guarantee educational improvement unless supported by an empathetic and context-sensitive response from educators.

The primary contribution of this research lies in its conceptual and methodological integration. Conceptually, it advances the understanding of how predictive analytics can be repositioned from a reactive monitoring tool to a proactive educational strategy. Methodologically, it combines machine learning precision with qualitative validation, producing a robust framework that bridges algorithmic prediction and human-centered pedagogy. This dual approach contributes to the emerging field of learning analytics by emphasizing the necessity of aligning technological innovation with ethical, instructional, and emotional dimensions of education. The model presented offers a replicable and scalable strategy for institutions aiming to implement AI-based early intervention systems within hybrid learning settings.

The research is limited by its reliance on institutional data from a single university and by the short duration of observation across two academic semesters. The findings may not fully represent variations in digital literacy, infrastructure, or cultural factors that influence hybrid learning effectiveness in other contexts. Future studies should employ longitudinal and cross-institutional designs to examine the sustainability of predictive interventions and their adaptability across different educational systems. Further exploration into affective analytics, algorithmic fairness, and real-time adaptive interventions is also recommended to refine ethical

AI integration in higher education and to ensure that predictive models truly foster equitable learning outcomes.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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