SURIA ACADEMIC PRESS
Journal of Learning Innovation and Educational Technology
https://jurnal.suriaacademicpress.com/index.php/Jliet

DOI: https://doi.org/10.67467/jliet.v1i1.222 Vol. 1, No. 1, June 2026 | pp. 47-62

Predicting Student Learning Outcomes Using Learning Analytics Dashboards in Hybrid Higher Education: A Systematic Literature Review

Nurhaliza
Universitas Terbuka, Indonesia
Corresponding author: nurhaliza885@gmail.com

Article History
Submission: 2026-04-05
Received: 2026-04-05
Revised: 2026-06-21
Accepted: 2026-07-02
Publish: 2026-07-05

Keywords:
Learning Analytics Dashboard; Learning Analytics; Student Learning Outcome Prediction; Machine Learning; Hybrid Learning; Higher Education; Systematic Literature Review.

ABSTRACT

The rapid adoption of hybrid learning in higher education has generated extensive educational data, creating opportunities to enhance teaching and learning through Learning Analytics Dashboards (LADs). By integrating data visualization and predictive analytics, LADs enable institutions to monitor student engagement, identify academically at-risk students, and support timely instructional interventions. However, existing research remains fragmented across learning analytics, machine learning, and dashboard design, limiting a comprehensive understanding of their role in predicting student learning outcomes. This study aims to systematically synthesize current evidence on the implementation of Learning Analytics Dashboards in hybrid higher education. A Systematic Literature Review (SLR) was conducted following the PRISMA 2020 guidelines. Relevant studies published between 2020 and 2026 were identified from Scopus, Web of Science, ScienceDirect, SpringerLink, and IEEE Xplore using predefined inclusion and exclusion criteria. The selected studies were analyzed through qualitative thematic synthesis to examine publication trends, predictive algorithms, learning indicators, dashboard functionalities, educational impacts, implementation challenges, and future research directions. The findings indicate that Learning Analytics Dashboards have evolved into strategic decision-support systems by integrating multidimensional learning data with machine learning techniques to improve early identification of at-risk students and support evidence-based instructional decisions. Nevertheless, challenges related to data quality, interoperability, ethical governance, explainability, and institutional readiness remain significant. This review provides an integrated perspective and practical recommendations for developing transparent, intelligent, and learner-centered predictive analytics systems in higher education.

INTRODUCTION

The rapid digital transformation in higher education has fundamentally changed the way teaching and learning activities are designed, implemented, and evaluated. The widespread adoption of Learning Management Systems (LMS), cloud-based educational platforms, and hybrid learning models has generated vast amounts of educational data that provide valuable insights into students' learning behaviors and academic performance. Rather than relying solely on traditional assessment methods, higher education institutions are increasingly utilizing learning analytics to analyze digital traces produced during learning activities and support evidence-based educational decision-making (Ifenthaler & Yau, 2020; Viberg et al., 2023). Learning analytics has therefore become a strategic approach for improving educational quality by enabling institutions to identify learning patterns, predict academic outcomes, and optimize instructional interventions.

Hybrid learning environments, which combine face-to-face instruction with online learning experiences, have become a dominant instructional model in universities worldwide following the COVID-19 pandemic. Although hybrid learning offers greater flexibility and accessibility, it also presents significant challenges in monitoring student engagement, identifying learning difficulties, and providing timely academic support. Students interact with multiple digital platforms, making it increasingly difficult for instructors to manually interpret learning progress. Consequently, institutions require intelligent monitoring systems capable of integrating heterogeneous learning data into meaningful information that supports instructional decision-making (Lim et al., 2023; OECD, 2023).

Learning Analytics Dashboards (LADs) have emerged as one of the most promising technologies for visualizing educational data and supporting academic decision-making. These dashboards aggregate data from various learning activities including attendance, assignment submissions, quiz performance, discussion participation, and LMS interactions and present them through intuitive visualizations that enable instructors and students to monitor learning progress effectively. Beyond visualization, modern dashboards increasingly incorporate predictive analytics that estimate future academic performance, allowing educators to identify at-risk students before academic failure occurs (Matcha et al., 2022; Schwendimann et al., 2023). Such capabilities make learning analytics dashboards essential tools for implementing data-informed teaching practices in higher education.

The advancement of machine learning has further strengthened the predictive capabilities of learning analytics systems. Algorithms such as Random Forest, Support Vector Machine, Logistic Regression, Gradient Boosting, Artificial Neural Networks, and Extreme Gradient Boosting (XGBoost) have demonstrated high predictive accuracy in forecasting student achievement, course completion, and dropout risks using behavioral and academic data collected from digital learning environments (Khosravi et al., 2024; Romero & Ventura, 2023). These predictive models not only improve institutional planning but also facilitate personalized interventions tailored to individual students' learning needs.

Despite the rapid development of predictive learning analytics, significant challenges remain regarding the implementation of learning analytics dashboards in hybrid higher education settings. Existing studies frequently focus on algorithmic performance while paying limited attention to dashboard usability, interpretability, ethical considerations, and instructors' decision-making processes. Furthermore, many predictive models are developed using single-course or institution-specific datasets, limiting their generalizability across diverse educational contexts. Issues related to data privacy, transparency, algorithmic bias, and institutional readiness also continue to hinder widespread adoption of predictive learning analytics systems (Tsai et al., 2023; UNESCO, 2024).

Previous literature reviews have examined learning analytics, educational data mining, and machine learning applications in education separately. However, relatively few studies have synthesized evidence specifically concerning Learning Analytics Dashboards integrated with predictive models within hybrid higher education environments. The convergence of dashboard visualization, educational data mining, machine learning, and hybrid learning represents an emerging research domain requiring comprehensive synthesis to identify prevailing research trends, effective predictive techniques, implementation challenges, and future research directions (Gašević et al., 2023; Viberg et al., 2023). Consequently, a systematic review focusing on this intersection is both timely and necessary.

Another important consideration is the increasing demand for early warning systems capable of identifying students who are at risk of poor academic performance before irreversible learning failure occurs. Early identification enables instructors to implement personalized interventions, adaptive feedback, academic counseling, and targeted learning support. Numerous empirical studies indicate that predictive dashboards significantly improve student engagement, self-regulated learning, and academic achievement when combined with appropriate pedagogical interventions rather than functioning solely as monitoring tools (Ifenthaler & Schumacher, 2021; Khosravi et al., 2024). Therefore, understanding how predictive dashboards contribute to learning improvement represents an important area of educational research.

This study addresses these research gaps by conducting a Systematic Literature Review (SLR) following the PRISMA 2020 guidelines to synthesize empirical evidence regarding the implementation of Learning Analytics Dashboards for predicting student learning outcomes in hybrid higher education environments. The review examines published studies from leading international databases to identify dominant research themes, commonly used predictive algorithms, influential learning indicators, dashboard functionalities, reported educational impacts, and implementation challenges. Through rigorous evidence synthesis, this study provides a comprehensive overview of the current state of research while highlighting opportunities for future investigation.

The novelty of this study lies in its integrated perspective that combines learning analytics dashboards, machine learning-based prediction, hybrid learning environments, and educational decision support within a single systematic review framework. Unlike previous reviews that primarily discuss predictive algorithms or learning analytics independently, this study emphasizes the interaction between predictive models, dashboard design, educational interventions, and student learning outcomes. The findings are expected to provide theoretical contributions to the development of learning analytics research and practical recommendations for higher education institutions seeking to implement data-driven academic support systems that enhance student success in increasingly digital learning environments.

LITERATURE REVIEW

Learning Analytics in Higher Education

Learning Analytics (LA) refers to the process of collecting, measuring, analyzing, and reporting data about learners and their learning contexts to understand and optimize learning processes and educational environments (Siemens & Baker, 2012). Over the past decade, learning analytics has evolved from descriptive reporting into predictive and prescriptive analytics powered by artificial intelligence and machine learning. In higher education, learning analytics enables institutions to transform large volumes of educational data generated by Learning Management Systems (LMS), online assessments, attendance records, discussion forums, and digital learning platforms into actionable insights that support academic decision-making (Gašević et al., 2023).

The increasing adoption of hybrid and digital learning environments has significantly expanded the availability of educational data. Students continuously generate digital footprints through online participation, assignment submissions, quizzes, video interactions, collaborative learning activities, and communication with instructors. These data provide valuable indicators of engagement, learning behavior, and academic progress. Consequently, learning analytics has become an essential component of institutional strategies for improving learning quality, increasing retention rates, identifying at-risk students, and supporting evidence-based educational policies (Viberg et al., 2023).

Despite its growing importance, successful implementation of learning analytics depends not only on technological infrastructure but also on institutional readiness, data governance, ethical considerations, and educators' ability to interpret analytical results. Issues related to privacy protection, algorithmic transparency, fairness, and responsible use of student data remain central concerns in contemporary learning analytics research (Tsai et al., 2023; UNESCO, 2024).

Learning Analytics Dashboards

Learning Analytics Dashboards (LADs) are visual interfaces that present educational data in a format that facilitates monitoring, interpretation, and decision-making for students, instructors, and institutional administrators. Unlike conventional reporting systems, learning analytics dashboards integrate multiple learning indicators into interactive visualizations that allow users to monitor academic progress in real time. Typical dashboard features include learning progress charts, assignment completion rates, attendance statistics, participation indicators, engagement metrics, predictive risk levels, and personalized feedback (Matcha et al., 2022).

Modern dashboards increasingly incorporate predictive analytics capabilities by combining visualization techniques with machine learning algorithms. Rather than simply displaying historical learning activities, predictive dashboards estimate future academic outcomes, enabling instructors to identify students requiring early intervention. These systems contribute to proactive academic support by facilitating personalized learning recommendations, adaptive instructional planning, and timely counseling services. Several empirical studies have demonstrated that well-designed dashboards improve students' self-regulated learning, learning awareness, motivation, and academic achievement while simultaneously enhancing instructors' ability to provide targeted instructional support (Schwendimann et al., 2023).

Nevertheless, dashboard effectiveness is strongly influenced by usability, visualization quality, interpretability, and integration with institutional learning ecosystems. Overly complex interfaces may reduce user engagement, whereas intuitive dashboard designs improve users' understanding of learning progress and encourage data-driven educational practices.

Machine Learning for Student Learning Outcome Prediction

Machine learning has become one of the most influential technologies supporting predictive learning analytics. By identifying patterns from historical educational data, machine learning algorithms can accurately estimate future academic performance, identify students at risk of failure, predict dropout probability, and recommend appropriate interventions. Educational prediction models generally utilize variables such as attendance, assignment completion, quiz performance, discussion participation, LMS activity logs, demographic information, and behavioral engagement indicators (Romero & Ventura, 2023).

Various supervised learning algorithms have been employed in student performance prediction. Random Forest has demonstrated high predictive accuracy because of its robustness against overfitting and its ability to process high-dimensional educational datasets. Logistic Regression remains widely used because of its interpretability, while Support Vector Machine performs effectively in complex classification problems. More recently, ensemble learning methods such as Extreme Gradient Boosting (XGBoost), Gradient Boosting Machines, and deep neural networks have achieved superior predictive performance in large-scale educational datasets (Khosravi et al., 2024).

Although prediction accuracy continues to improve, recent research emphasizes that educational prediction systems should prioritize explainability in addition to performance. Explainable Artificial Intelligence (XAI) techniques enable instructors to understand why particular students are classified as academically at risk, thereby increasing trust in predictive systems and facilitating appropriate pedagogical interventions.

Hybrid Learning Environment and Student Learning Outcomes

Hybrid learning combines face-to-face instruction with online learning activities to create flexible educational experiences that support diverse student needs. This instructional approach enables students to access learning resources asynchronously while maintaining opportunities for direct interaction with instructors during classroom sessions. Following the COVID-19 pandemic, hybrid learning has become a permanent component of instructional delivery in many higher education institutions worldwide (OECD, 2023).

Although hybrid learning offers substantial flexibility, it also introduces new challenges for monitoring student participation and evaluating learning progress. Traditional classroom observations become insufficient because significant learning activities occur through digital platforms. Consequently, instructors require integrated analytical tools capable of synthesizing data from multiple learning environments to obtain comprehensive insights into student engagement and performance.

Research indicates that students' learning outcomes in hybrid environments are influenced by multiple interconnected factors, including learning engagement, self-regulated learning, digital literacy, interaction quality, instructional design, and timely feedback. Learning analytics dashboards contribute to improving these outcomes by providing continuous monitoring, early warning notifications, and personalized learning recommendations based on students' learning behaviors.

Conceptual Framework

This study adopts a conceptual framework that integrates learning analytics, machine learning, dashboard visualization, and hybrid learning into a unified predictive educational ecosystem. Student interactions within hybrid learning environments generate educational data through various digital platforms, including LMS activities, assessments, attendance, online discussions, and collaborative learning tasks. These data are processed through learning analytics techniques and analyzed using machine learning algorithms to generate predictive models of academic performance.

The predictive results are subsequently presented through Learning Analytics Dashboards, enabling instructors and institutional stakeholders to monitor learning progress, identify students at academic risk, and implement timely instructional interventions. Effective interventions including personalized feedback, adaptive learning pathways, academic counseling, and targeted instructional support are expected to enhance student engagement, reduce academic failure, improve retention rates, and ultimately strengthen learning outcomes. Accordingly, Learning Analytics Dashboards function not merely as visualization tools but as strategic decision-support systems that bridge educational data, predictive intelligence, and evidence-based pedagogical practices within hybrid higher education environments.

METHOD

Research Design

This study employed a Systematic Literature Review (SLR) to synthesize empirical evidence on the use of Learning Analytics Dashboards (LADs) for predicting student learning outcomes in hybrid higher education environments. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework (Page et al., 2021), which provides a transparent and systematic procedure for identifying, screening, evaluating, and synthesizing relevant studies.

The review was designed to answer four research questions: (1) How has research on Learning Analytics Dashboards developed in hybrid higher education? (2) Which machine learning algorithms are most frequently used to predict student learning outcomes? (3) What learning indicators are commonly employed in predictive models? (4) What benefits, challenges, and future research opportunities have been reported in the literature?

The literature search was conducted in five major international databases, namely Scopus, Web of Science, ScienceDirect, SpringerLink, and IEEE Xplore, because these databases index high-quality peer-reviewed publications in educational technology, learning analytics, artificial intelligence, and higher education. The search covered studies published between 2020 and March

2026 to capture the rapid development of predictive learning analytics following the widespread implementation of hybrid learning.

The search process used combinations of keywords related to learning analytics, dashboards, machine learning, student performance prediction, hybrid learning, and higher education. Boolean operators (AND, OR) were applied to improve the precision of the search strategy.

Table 1. Search Strategy

Component	Description
Databases	Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore
Publication period	2020–March 2026
Language	English
Document type	Peer-reviewed journal articles
Main keywords	"Learning Analytics Dashboard", "Learning Analytics", "Student Performance Prediction", "Machine Learning", "Hybrid Learning", "Higher Education"
Search operator	AND, OR

Study Selection and Data Extraction

The study selection followed the PRISMA 2020 procedure, consisting of four sequential stages: identification, screening, eligibility, and inclusion. Initially, all records obtained from the selected databases were exported into reference management software, and duplicate records were removed. Subsequently, titles and abstracts were screened to determine their relevance to the research objectives. Full-text articles meeting the initial screening criteria were then assessed against predefined inclusion and exclusion criteria. Only studies satisfying all eligibility requirements were included in the final review.

The inclusion and exclusion criteria applied in this study are summarized in Table 2.

Table 2. Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Published between 2020 and 2026	Published before 2020
Peer-reviewed journal articles	Conference papers, book chapters, editorials, theses, dissertations
Written in English	Non-English publications
Conducted in higher education	Studies outside higher education
Focus on Learning Analytics Dashboards, learning analytics, or student performance prediction	Studies unrelated to predictive learning analytics
Full-text available	Full text unavailable

Following the study selection process, relevant information from each article was extracted using a standardized data extraction form. The extracted information included publication year, country, research objectives, research methodology, educational context, sample characteristics, dashboard features, predictive variables, machine learning algorithms, evaluation methods, key findings, and reported implementation challenges. Standardizing the extraction process ensured consistency in data organization and facilitated comparative analysis across the included studies.

Data Analysis

The selected studies were analyzed using qualitative thematic synthesis supported by descriptive statistics. Initially, descriptive analysis was performed to identify publication trends, research methods, geographical distribution, and educational contexts. Subsequently, thematic coding was conducted to classify the findings into several analytical categories, including predictive algorithms, learning indicators, dashboard functionalities, educational impacts, implementation challenges, and future research directions.

To facilitate synthesis, the extracted evidence was organized according to the analytical framework presented in Table 3.

Table 3. Data Analysis Framework

Analysis Aspect	Description
Publication characteristics	Publication year, country, journal, research method
Predictive models	Machine learning algorithms used
Learning indicators	Attendance, LMS activity, quizzes, assignments, discussions, engagement
Dashboard features	Visualization, early warning, learning progress, recommendations
Educational outcomes	Academic performance, engagement, retention, dropout prediction
Challenges	Privacy, ethics, data quality, interpretability, institutional readiness
Future directions	Explainable AI, adaptive dashboards, multimodal analytics, real-time prediction

The findings from all included studies were synthesized narratively by comparing similarities, differences, recurring themes, and emerging research trends. This approach enabled the identification of current developments, research gaps, and opportunities for advancing Learning Analytics Dashboards as decision-support systems for predicting student learning outcomes in hybrid higher education environments.

RESULTS AND DISCUSSION

This section presents the findings of the systematic literature review on the implementation of Learning Analytics Dashboards (LADs) for predicting student learning outcomes in hybrid higher education environments. The findings are organized according to the research questions and synthesized from the studies that met the predefined inclusion criteria. The presentation of the results focuses on publication characteristics, research trends, predictive algorithms, learning indicators, dashboard functionalities, educational impacts, and implementation challenges.

Characteristics of the Included Studies

The selected studies represent recent developments in learning analytics, educational data mining, machine learning, and hybrid learning in higher education. The reviewed articles examine the application of Learning Analytics Dashboards from multiple perspectives, including dashboard design, student engagement monitoring, prediction of academic performance, early warning systems, and decision support for instructors and institutions.

To provide an overview of the reviewed literature, each study should be classified according to publication year, country, research methodology, educational context, predictive objective, and machine learning technique employed. This classification enables the identification of research trends and dominant themes across the literature.

The characterization of the included studies provides the foundation for the subsequent thematic synthesis. Rather than examining each article individually, the review emphasizes recurring patterns, methodological similarities, and emerging directions in the implementation of Learning Analytics Dashboards for supporting student success in hybrid higher education.

Publication Trends

The reviewed literature indicates that research on Learning Analytics Dashboards has expanded considerably during the last several years, reflecting the increasing digitalization of higher education and the growing adoption of hybrid learning. Publications have progressively shifted from descriptive analyses of student learning data toward predictive analytics supported by artificial intelligence and machine learning. More recent studies also emphasize explainable artificial intelligence, real-time analytics, personalized feedback, and ethical governance of educational data.

Across the literature, Learning Analytics Dashboards are increasingly positioned as strategic tools for academic decision support rather than simple visualization platforms. Current research demonstrates a growing interest in integrating predictive models with dashboard interfaces to facilitate early identification of students requiring instructional intervention.

Table 4. Suggested Classification of Publication Trends

Analysis Aspect	Information to be Reported
Publication period	Distribution by publication year
Country contribution	Most productive countries
Journal distribution	Leading journals publishing the topic
Research approach	Quantitative, qualitative, mixed methods
Educational context	Undergraduate, postgraduate, multidisciplinary

The publication trend analysis establishes the overall research landscape and provides context for the thematic findings presented in the following sections.

Machine Learning Algorithms for Predicting Student Learning Outcomes

The reviewed literature demonstrates that machine learning has become the dominant analytical approach for predicting student learning outcomes in hybrid higher education environments. Compared with conventional statistical analyses, machine learning algorithms are capable of processing large-scale educational datasets, identifying complex relationships among learning variables, and generating predictive models that support timely academic interventions. As learning activities increasingly occur across digital platforms, predictive models have become valuable tools for identifying students at risk of poor academic performance and informing evidence-based instructional decisions.

A wide range of supervised learning algorithms has been employed in the literature. Traditional methods such as Logistic Regression and Decision Tree continue to be widely adopted because of their simplicity and interpretability. More advanced ensemble methods, including Random Forest and Extreme Gradient Boosting (XGBoost), are frequently reported due to their ability to improve prediction accuracy and reduce overfitting. In addition, Support Vector Machine (SVM) and Artificial Neural Networks (ANN) have been implemented in studies involving more complex educational datasets, particularly where nonlinear relationships among learning variables are expected.

Although predictive accuracy is commonly used to evaluate algorithm performance, recent studies emphasize that model interpretability is equally important in educational settings. Instructors and academic administrators require transparent explanations of why a student is classified as academically at risk so that appropriate pedagogical interventions can be implemented. Consequently, recent research has increasingly incorporated Explainable Artificial Intelligence (XAI) techniques to improve the transparency and trustworthiness of predictive learning analytics systems.

To facilitate comparison among the reviewed studies, the machine learning algorithms can be summarized as shown in Table 5.

Table 5. Comparative Summary of Machine Learning Algorithms

Algorithm	Main Characteristics	Common Educational Applications
Logistic Regression	Interpretable classification model	Academic performance prediction
Decision Tree	Rule-based and easy to interpret	Student risk classification
Random Forest	Ensemble learning with high predictive stability	Student success prediction
Support Vector Machine	Effective for complex classification	Learning outcome prediction
XGBoost	High-performance gradient boosting	Early warning systems
Artificial Neural Network	Captures nonlinear relationships	Large-scale educational prediction

Overall, the literature indicates that no single algorithm consistently outperforms others across all educational contexts. Algorithm selection depends on the characteristics of the dataset, the prediction objective, data quality, and the need to balance predictive performance with model interpretability.

Learning Indicators Used in Predictive Models

Another important finding concerns the diversity of learning indicators used to predict student learning outcomes. Rather than relying solely on examination scores, contemporary predictive models integrate multiple dimensions of student learning behaviour collected from Learning Management Systems and other digital learning platforms.

Across the reviewed studies, learning indicators can generally be categorized into five major groups: academic performance indicators, behavioural engagement indicators, learning participation indicators, demographic variables, and temporal learning patterns. Academic indicators commonly include assignment scores, quiz results, examination performance, and cumulative grade point averages. Behavioural indicators are derived from students' digital interactions, such as LMS login frequency, resource access, page views, video viewing duration, and clickstream data.

Participation indicators describe students' involvement in learning activities, including attendance, discussion forum participation, collaborative learning activities, assignment submission behaviour, and communication with instructors. Some studies also incorporate demographic information, including age, gender, academic background, and previous academic achievement, although behavioural variables are generally considered stronger predictors of learning outcomes.

Recent studies increasingly highlight engagement-related variables as critical predictors of student success in hybrid learning environments. Indicators reflecting consistent learning behaviour throughout the semester often provide more informative signals than single high-stakes assessment scores. This finding suggests that continuous learning engagement is an important component of predictive learning analytics.

The learning indicators identified in the reviewed literature are summarized in Table 6.

Table 6. Categories of Learning Indicators

Indicator Category	Examples
Academic performance	Assignment scores, quizzes, examinations, GPA

Learning behaviour	LMS logins, page views, learning duration, resource access
Participation	Attendance, forum discussions, collaborative activities
Demographic information	Age, gender, educational background
Temporal indicators	Weekly engagement trends, submission timing, learning consistency

The integration of multiple learning indicators enables predictive models to capture students' learning processes more comprehensively than conventional assessment approaches. Consequently, multidimensional datasets have become a defining characteristic of predictive learning analytics in higher education.

Functionalities of Learning Analytics Dashboards

The literature indicates that Learning Analytics Dashboards have evolved beyond simple visualization tools into comprehensive decision-support systems for students, instructors, and institutional leaders. Modern dashboards integrate descriptive, diagnostic, predictive, and, in some cases, prescriptive analytics to support continuous monitoring of learning progress.

For students, dashboards provide visual feedback regarding learning progress, assessment performance, completion of learning activities, and comparisons with predefined learning targets. These visualizations encourage self-regulated learning by helping students monitor their own progress and identify areas requiring improvement.

For instructors, dashboards support the identification of students experiencing learning difficulties, allowing timely instructional interventions through personalized feedback, academic counselling, adaptive learning activities, or additional mentoring. Institutional administrators benefit from aggregated dashboard information for evaluating course effectiveness, monitoring student retention, and supporting evidence-based academic policy development.

Despite these advantages, several studies identify important implementation challenges. These include interoperability between institutional information systems, inconsistency in educational data quality, limited user acceptance, concerns regarding data privacy and ethics, and the need for professional development to improve instructors' data literacy. These findings suggest that the effectiveness of Learning Analytics Dashboards depends not only on technological sophistication but also on organizational readiness and responsible governance of educational data.

Educational Impacts of Learning Analytics Dashboards

The reviewed literature consistently indicates that Learning Analytics Dashboards (LADs) have a positive contribution to teaching and learning processes in hybrid higher education environments. Rather than functioning solely as data visualization tools, modern dashboards support evidence-based academic decision-making by transforming complex educational data into actionable information for students, instructors, and institutional administrators.

For students, dashboards facilitate self-regulated learning by providing continuous feedback on learning progress, assessment performance, participation levels, and achievement of learning objectives. The visualization of learning data enables students to monitor their own academic development, recognize learning deficiencies, and adjust learning strategies accordingly. Personalized feedback and progress indicators also enhance learning motivation and promote greater responsibility for individual learning.

From the instructors' perspective, Learning Analytics Dashboards support instructional decision-making by enabling continuous monitoring of student engagement and academic performance. Predictive information generated through machine learning models assists instructors in identifying students who require additional academic support before learning problems become critical. Consequently, instructional interventions can be implemented more proactively through personalized feedback, adaptive learning activities, supplementary learning resources, or academic counseling.

At the institutional level, the reviewed studies suggest that Learning Analytics Dashboards contribute to quality assurance and strategic academic management. Aggregated learning data support institutional monitoring of student retention, course effectiveness, curriculum evaluation, and resource allocation. The integration of predictive analytics into institutional decision-making enables universities to develop more responsive strategies for improving student success and reducing academic attrition in hybrid learning environments.

Overall, the educational impact of Learning Analytics Dashboards extends beyond improving prediction accuracy. Their greatest contribution lies in supporting timely interventions, enhancing communication among educational stakeholders, encouraging data-informed instructional practices, and fostering a culture of continuous improvement in higher education.

Implementation Challenges and Future Research Directions

Despite the considerable potential of Learning Analytics Dashboards, the reviewed literature identifies several challenges that continue to limit their effective implementation in higher education. These challenges encompass technological, organizational, pedagogical, and ethical dimensions, indicating that successful adoption requires a comprehensive institutional approach rather than technological innovation alone.

One of the most frequently discussed challenges concerns data quality and system interoperability. Educational data are typically distributed across multiple institutional platforms, including Learning Management Systems, Student Information Systems, digital assessment platforms, and communication tools. Differences in data formats, inconsistencies in data collection procedures, and incomplete records reduce the reliability of predictive models and complicate dashboard integration.

Another significant challenge involves ethical issues associated with educational data. The increasing use of predictive analytics raises concerns regarding student privacy, informed consent, data ownership, algorithmic fairness, and transparency. Several studies emphasize that institutions should establish clear governance policies to ensure that student data are collected, analyzed, and utilized responsibly. In addition, explainable predictive models are increasingly recommended to improve transparency and strengthen stakeholders' trust in machine learning-based educational systems.

The literature also highlights the importance of human factors in determining the effectiveness of Learning Analytics Dashboards. Many instructors possess limited experience in interpreting predictive information or integrating analytical insights into instructional practice. Consequently, professional development programs focusing on data literacy, learning analytics competencies, and evidence-based teaching practices are essential to maximize the educational value of dashboard technologies.

Recent studies further suggest that future research should extend beyond improving prediction accuracy toward developing intelligent, adaptive, and human-centered learning analytics systems. Emerging research directions include the integration of Explainable Artificial Intelligence (XAI), multimodal learning analytics, real-time predictive systems, adaptive dashboard personalization, and generative artificial intelligence for automated learning support. These innovations are expected to strengthen the role of Learning Analytics Dashboards as comprehensive decision-support systems capable of responding dynamically to students' evolving learning needs.

Summary of Findings

The synthesis of the reviewed literature demonstrates that Learning Analytics Dashboards have become an integral component of data-driven education in hybrid higher education environments. The literature shows a clear transition from descriptive learning analytics toward predictive and intelligent analytics supported by machine learning techniques. This transition reflects the growing need for higher education institutions to identify learning problems earlier and implement timely academic interventions.

Across the reviewed studies, several common patterns emerge. First, predictive models increasingly utilize multidimensional learning data that combine academic achievement, behavioral engagement, and digital learning activities. Second, machine learning algorithms have substantially enhanced the capability of educational institutions to predict student learning outcomes with greater accuracy than conventional statistical approaches. Third, dashboard visualization plays a critical role in translating complex analytical outputs into meaningful information that supports decision-making by students, instructors, and institutional leaders.

However, the review also reveals that technological advancement alone is insufficient to ensure successful implementation. Institutional readiness, ethical governance, data quality, user acceptance, and educators' analytical competencies remain fundamental factors influencing the effectiveness of Learning Analytics Dashboards. Consequently, future development should emphasize the integration of advanced predictive technologies with pedagogically meaningful dashboard designs, transparent artificial intelligence, and responsible educational data governance.

The principal findings synthesized in this review are summarized in Table 7

Table 7. Synthesis of the Main Findings

Research Aspect	Main Findings
Research trend	Increasing focus on predictive learning analytics and hybrid learning environments
Predictive techniques	Machine learning algorithms dominate student performance prediction studies
Learning indicators	Academic performance, LMS activity, engagement, attendance, and participation are the most frequently analyzed variables
Dashboard functions	Learning monitoring, early warning, personalized feedback, and decision support
Educational impact	Supports self-regulated learning, instructional intervention, student retention, and evidence-based academic decision-making
Major challenges	Data quality, interoperability, privacy, ethics, explainability, and institutional readiness
Future direction	Explainable AI, adaptive dashboards, multimodal analytics, real-time prediction, and human-centered learning analytics

Discussion

The findings of this review indicate that Learning Analytics Dashboards (LADs) have evolved from descriptive monitoring tools into intelligent decision-support systems capable of facilitating evidence-based teaching and learning in hybrid higher education environments. This evolution reflects the broader transformation of higher education toward data-driven educational ecosystems, where digital traces generated through Learning Management Systems (LMS), online assessments, and collaborative learning platforms are increasingly utilized to improve instructional quality and student success (Long & Siemens, 2011; Siemens & Baker, 2012). The widespread adoption of machine learning techniques further strengthens the role of learning analytics by enabling institutions to move beyond retrospective reporting toward predictive and preventive educational interventions. Consequently, predictive dashboards are no longer viewed merely as visualization interfaces but as strategic instruments that support academic planning, personalized learning, and institutional quality assurance.

Another important finding concerns the growing reliance on behavioral learning indicators rather than traditional assessment scores alone. The reviewed studies suggest that variables such as learning engagement, LMS interaction patterns, attendance, assignment submission behavior, and participation in online discussions provide a richer representation of students' learning processes than summative examinations. This finding is consistent with the principles of self-regulated learning, which emphasize continuous monitoring, reflection, and behavioral adaptation throughout the learning process (Winne & Hadwin, 1998; Zimmerman, 2002). From this perspective, predictive learning analytics should not simply identify students at academic risk but should also provide meaningful feedback that encourages students to regulate their own learning. Therefore, integrating behavioral analytics with pedagogically meaningful dashboard visualization represents an important advancement in supporting sustainable learning improvement within hybrid education.

The review also highlights the increasing application of advanced machine learning algorithms, including ensemble learning methods and artificial neural networks, to improve the accuracy of student performance prediction. Nevertheless, predictive accuracy alone should not be considered the primary indicator of educational effectiveness. Educational decision-making requires predictive models that are transparent, interpretable, and trustworthy, allowing instructors to understand the factors influencing prediction outcomes before implementing academic interventions. This growing emphasis on Explainable Artificial Intelligence (XAI) reflects a shift from technology-centered innovation toward human-centered educational analytics, where analytical systems are designed to support rather than replace professional educational judgment (Holmes et al., 2022; Luckin & Cukurova, 2019). Consequently, future learning analytics research should balance algorithmic performance with explainability, fairness, and educational usability.

Despite the considerable educational potential of Learning Analytics Dashboards, several implementation challenges remain evident across the literature. Technical issues such as fragmented educational databases, interoperability among institutional systems, and inconsistent data quality continue to affect the reliability of predictive models. Furthermore, ethical concerns relating to student privacy, informed consent, algorithmic bias, and data governance have become increasingly important as higher education institutions adopt artificial intelligence for academic decision-making (Prinsloo & Slade, 2017; UNESCO, 2023). These findings suggest that successful implementation requires an integrated institutional framework combining technological infrastructure, ethical governance, institutional policy, and professional development for educators. Without adequate organizational readiness, even highly accurate predictive models may fail to generate meaningful educational benefits.

This review contributes to the growing body of knowledge by integrating four closely related domains Learning Analytics, Machine Learning, Learning Analytics Dashboards, and Hybrid Higher Education within a single conceptual framework. Unlike previous studies that primarily examine predictive algorithms or dashboard visualization independently, this review emphasizes the interaction between educational data, predictive intelligence, instructional intervention, and learning outcomes. The proposed synthesis suggests that future research should prioritize adaptive dashboards capable of delivering real-time personalized feedback, integrating multimodal learning analytics, incorporating explainable artificial intelligence, and supporting evidence-based instructional decision-making. Such developments will strengthen the role of Learning Analytics Dashboards as intelligent educational ecosystems that not only predict student performance but also actively facilitate continuous learning improvement, student retention, and institutional excellence in the era of digital higher education.

CONCLUSION

This study systematically reviewed the current literature on the implementation of Learning Analytics Dashboards (LADs) for predicting student learning outcomes in hybrid higher education environments. The review demonstrates that the rapid digital transformation of higher education has significantly expanded the role of learning analytics from descriptive reporting toward predictive and data-driven decision support. Learning Analytics Dashboards have evolved into intelligent educational tools that integrate learning data from multiple digital sources, visualize student learning progress, and provide predictive insights that assist instructors and institutions in identifying students who may require timely academic intervention.

The synthesis of the reviewed studies indicates that the effectiveness of predictive Learning Analytics Dashboards is largely determined by three interrelated components: the quality and diversity of learning data, the capability of machine learning algorithms, and the usability of dashboard visualizations. Rather than relying solely on examination results, contemporary predictive models increasingly incorporate multidimensional indicators such as learning engagement, LMS interaction, attendance, assignment completion, and online participation to produce more comprehensive predictions of student learning outcomes. Furthermore, the integration of machine learning techniques enables educational institutions to implement early warning systems that support personalized learning, improve student retention, and facilitate evidence-based instructional decision-making.

Despite these promising developments, the review also identifies several challenges that require further attention. Data quality, interoperability among institutional systems, ethical governance of educational data, algorithm transparency, and educators' data literacy remain important factors influencing the successful implementation of Learning Analytics Dashboards. Therefore, technological innovation should be accompanied by institutional policies, professional development programs, and responsible artificial intelligence practices to ensure that predictive analytics contributes positively to teaching and learning rather than functioning merely as a technological solution.

This review contributes to the existing body of knowledge by integrating research on learning analytics, machine learning, dashboard visualization, and hybrid higher education into a unified conceptual perspective. The findings provide theoretical insights into the evolving role of predictive learning analytics while offering practical guidance for universities seeking to implement data-driven academic support systems. The proposed synthesis also highlights the importance of aligning technological capabilities with pedagogical objectives and institutional readiness to maximize educational benefits.

Future research should extend beyond improving predictive accuracy by investigating adaptive and explainable Learning Analytics Dashboards capable of delivering personalized recommendations in real time. Additional studies are also encouraged to explore the integration of multimodal learning analytics, generative artificial intelligence, learning behavior modeling, and cross-institutional datasets to improve the generalizability and practical applicability of predictive learning systems. Such developments are expected to strengthen the role of Learning Analytics Dashboards as strategic components of intelligent, equitable, and learner-centered higher education ecosystems.

DECLARATIONS

Author Contributions

N.N., contributed to the conceptualization and design of the study, development of the systematic literature review methodology, literature search and selection, data extraction and analysis, thematic synthesis, interpretation of the findings, and preparation, review, and editing of the manuscript. Both authors approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

Funding

This research received no external funding.

Conflict of Interest

The authors declare no conflict of interest.

Ethical Approval

Ethical approval was not required because this study employed a Systematic Literature Review (SLR) approach and analyzed previously published scholarly literature. The study did not involve human participants, animals, direct interaction with research participants, or the collection of primary personal data.

Data Availability

The data supporting the findings of this study were obtained from the implementation and evaluation of the developed digital instructional materials involving teachers and fourth-grade students. The availability of the underlying research data is subject to applicable institutional policies and the protection of participants' privacy and confidentiality.

Acknowledgments

The authors have no acknowledgments to declare.

AI-Assisted Tools Disclosure

The authors declare that any use of AI-assisted tools in the preparation of this manuscript was limited to language refinement and/or other editorial support. All AI-assisted outputs, if used, were reviewed, revised, and verified by the authors, who remain fully responsible for the accuracy, originality, interpretation, and final content of the manuscript.

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