OPEN ACCESS
Journal Neosantara Hybrid Learning
Vol. 3 No. 6. April 2025, pp. 367-378 DOI. 10.70177/jnhl.v3i6.2853

Research Article

PERSONALIZED HYBRID LEARNING THROUGH ARTIFICIAL INTELLIGENCE AND PREDICTIVE ANALYTICS: A SYSTEMATIC LITERATURE REVIEW

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Article Info
Received: June 25, 2025
Revised: August 11, 2025
Accepted: November 22, 2025
Online Version: Desember 31, 2025

Abstract
The increasing complexity of contemporary learning environments demands instructional approaches that are adaptive, data-driven, and responsive to diverse learner characteristics. This study aims to systematically examine the integration of artificial intelligence (AI) and predictive analytics in personalized hybrid learning and to identify its contributions to the broader development of educational science. Employing a systematic literature review methodology, peer-reviewed studies published between 2015 and 2024 were retrieved from Scopus, Web of Science, ERIC, and Google Scholar databases using predefined inclusion and exclusion criteria. The selected articles were analyzed through thematic synthesis to identify dominant patterns, strategies, and outcomes. The findings indicate that the integration of AI and predictive analytics enhances learning effectiveness by enabling adaptive content delivery, early identification of learning risks, and data-informed instructional decision-making within hybrid learning environments. The novelty of this study lies in its integrative perspective that positions AI and predictive analytics as a unified framework for personalized hybrid learning, rather than as isolated technological tools. Furthermore, the review highlights how predictive insights derived from learner data can support more responsive, equitable, and sustainable learning designs. The implications of this research suggest that the strategic application of AI-driven personalization and predictive analytics can advance pedagogical innovation, strengthen evidence-based educational practices, and contribute to the ongoing transformation of learning systems in response to the demands of digital and hybrid education.

Keywords: Artificial intelligence; Hybrid learning; Personalized learning; Predictive analytics; Systematic literature review

Journal Homepage https://research.adra.ac.id/index.php/jnhl ISSN: (P: 2987-2316) - (E: 2986-979X)
How to cite: Putri, R. M., Mardalena, Mardalena, & Nizam, Z. (2025). Personalized Hybrid Learning Through Artificial Intelligence and Predictive Analytics: A Systematic Literature Review. *Journal Neosantara Hybrid Learning, 3*(6), 367–378. https://doi.org/10.70177/jnhl.v3i6.2853
Published by: Yayasan Adra Karima Hubbi

INTRODUCTION

The rapid transformation of educational practices driven by digitalization and reinforced by post-pandemic learning reforms has fundamentally reshaped how teaching and learning are organized across educational contexts. One of the most significant outcomes of this transformation is the widespread adoption of hybrid learning, which combines face-to-face instruction with online learning modalities. Hybrid learning has increasingly been positioned as a dominant instructional model due to its capacity to enhance flexibility, expand access to learning resources, and accommodate diverse learning contexts. However, despite its growing popularity, recent studies indicate that many hybrid learning implementations remain largely standardized and content-centered, offering limited adaptability to individual learner characteristics and needs. As a result, the pedagogical potential of hybrid learning is often underutilized, particularly in addressing variations in learners' cognitive abilities, engagement levels, and learning trajectories (Hamid, 2024).

The persistence of uniform instructional designs within hybrid learning environments suggests a critical gap between technological infrastructure and pedagogical intelligence. While digital platforms generate vast amounts of learner data, these data are frequently underexploited in informing instructional decisions. Consequently, hybrid learning systems often function as static delivery mechanisms rather than dynamic learning environments capable of responding to learner diversity in real time. This limitation underscores the need for instructional models that can systematically leverage learner data to support adaptive, personalized, and evidence-based learning experiences in increasingly complex educational settings. To illustrate the gap between conventional hybrid learning designs and adaptive data-driven learning environments, Diagram 1 presents a conceptual overview of the limitations of uniform instructional models and the need for intelligent adaptation.

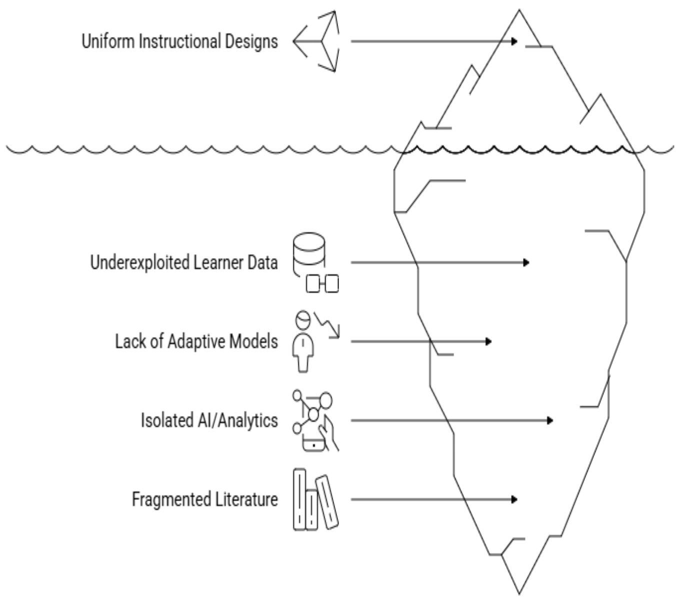

Figure 1 : Key Challenges in Hybrid Learning Environments

Figure 1 illustrates the key challenges in hybrid learning environments, highlighting persistent limitations related to instructional uniformity, low adaptability, and the insufficient utilization of learner data in pedagogical decision-making. Although hybrid learning integrates digital technologies with face-to-face instruction, its implementation often remains standardized and content-driven, offering limited responsiveness to individual learner differences. The diagram reflects a critical gap between technological infrastructure and pedagogical intelligence, where large volumes of learner data are generated but not systematically analyzed to inform instructional actions. Consequently, hybrid learning environments frequently function as static delivery systems rather than dynamic and adaptive learning ecosystems capable of supporting personalized and evidence-based learning experiences.

In response to these challenges, artificial intelligence (AI) has emerged as a strategic technological approach to enhancing learning adaptability through data-driven personalization and automated instructional support. AI-based learning systems are capable of processing large volumes of learner data to identify patterns in behavior, performance, and engagement. Empirical research demonstrates that such systems can facilitate adaptive content delivery, generate real-time feedback, recommend personalized learning pathways, and support intelligent tutoring functions (Wang, 2024). These capabilities enable instructional processes to shift from teacher-centered and one-size-fits-all approaches toward more responsive, learner-centered models. When effectively integrated, AI holds significant potential to transform hybrid learning from a relatively static instructional format into an adaptive learning ecosystem that continuously adjusts to learners' evolving needs.

Complementing AI-driven personalization, predictive analytics plays a crucial role in strengthening data-informed decision-making within educational environments. Predictive analytics involves the use of statistical and machine learning models to forecast future learning outcomes based on historical and real-time data. Recent empirical evidence suggests that predictive models can effectively identify early signs of academic risk, disengagement, or dropout by analyzing patterns such as learning behaviors, assessment performance, and interaction logs (Almalawi, 2024). These predictive insights allow educators and institutions to implement timely and targeted interventions, thereby shifting instructional practices from reactive responses to proactive support strategies. In hybrid learning contexts, predictive analytics offers a powerful mechanism for sustaining learner engagement and improving learning outcomes through early and informed action.

Despite the complementary strengths of artificial intelligence and predictive analytics, existing research has predominantly examined these approaches in isolation rather than as components of an integrated instructional framework. Current literature tends to focus on specific tools, platforms, or isolated applications without sufficiently exploring how personalization and prediction can be strategically aligned within hybrid learning environments. This fragmented body of research limits the development of comprehensive models capable of informing instructional design, learning support, and data-driven educational decision-making in a coherent and systematic manner (Holmes et al., 2022).

In response to this gap, the present study aims to systematically review recent research on the integration of artificial intelligence and predictive analytics in personalized hybrid learning. By synthesizing empirical findings and conceptual developments, this study seeks to identify dominant research trends, integration strategies, methodological approaches, and reported educational outcomes associated with data-driven personalization. The findings are expected to contribute to the advancement of educational science by providing a coherent conceptual foundation and practical insights that support the development of more responsive, equitable, and evidence-based hybrid learning systems capable of addressing diverse learner needs in contemporary educational landscapes.

RESEARCH METHOD

Research Design

This study employed a qualitative research approach using a Systematic Literature Review (SLR) design. The SLR approach was selected to ensure a structured, transparent, and replicable process in identifying, evaluating, and synthesizing existing research related to the integration of artificial intelligence and predictive analytics in personalized hybrid learning. Systematic literature review is widely recognized as an effective method for mapping research trends, identifying gaps, and developing conceptual frameworks within a field of study (Snyder, 2019). By applying this design, the study aims to provide a comprehensive synthesis of empirical and conceptual evidence relevant to data-driven personalization in hybrid learning environments.

Research Target/Subject

The research targets of this study were peer-reviewed journal articles that examine the use of artificial intelligence and predictive analytics in personalized and hybrid learning environments, as these approaches are increasingly recognized for their capacity to support adaptive instruction, learner engagement, and data-driven decision-making in education (Ouyang, Zheng, & Jiao, 2022). The research subjects consisted of scholarly articles published between 2019 and 2024, a timeframe chosen to capture recent empirical evidence and methodological advances related to AI-supported learning systems and learning analytics in higher education and blended learning contexts (Bond et al., 2021). Article selection was conducted using purposive sampling based on clearly defined inclusion and exclusion criteria to ensure that the reviewed studies were both methodologically rigorous and closely aligned with the research objectives (Lim et al., 2023). Inclusion criteria included articles published in international peer-reviewed journals, written in English, and explicitly addressing the application of artificial intelligence and/or predictive analytics within hybrid or personalized learning contexts. In contrast, exclusion criteria comprised conference proceedings without full-text availability, opinion-based papers, and studies that did not align with the focus on AI-enabled personalization or hybrid instructional models. This systematic selection strategy was applied to enhance the relevance, credibility, and academic quality of the reviewed literature.

Research Procedure

The research procedure was conducted through a series of structured and sequential stages to ensure methodological rigor, transparency, and replicability in conducting the systematic literature review on personalized hybrid learning through artificial intelligence and predictive analytics. The procedure was designed to systematically identify, screen, evaluate, and synthesize relevant scholarly evidence related to data-driven personalization in hybrid learning environments (Booth, Sutton, & Papaioannou, 2021). First, relevant keywords and Boolean search strings were systematically developed based on the research objectives and core concepts of artificial intelligence, predictive analytics, personalized learning, and hybrid learning. This step was essential to define the scope of the review and to optimize the retrieval of relevant studies that align with the focus of AI-supported personalization in hybrid educational contexts (Gough, Oliver, & Thomas, 2020).

Second, comprehensive literature searches were conducted across selected academic databases containing peer-reviewed publications in education and social sciences. This process aimed to ensure broad and balanced coverage of empirical and conceptual studies addressing the application of artificial intelligence and predictive analytics in personalized and hybrid learning settings (Zawacki-Richter, Marín, Bond, & Gouverneur, 2020). Third, all retrieved records were organized using a reference management system, after which duplicate articles were removed. Title and abstract screening was then performed to assess the relevance of the studies in relation to the predefined research questions, inclusion criteria, and thematic focus of the review (Aromataris & Munn, 2020).

Fourth, full-text articles that passed the initial screening were reviewed in detail using explicit inclusion and exclusion criteria to ensure methodological quality, conceptual relevance, and alignment with the objectives of examining AI-driven personalization and predictive analytics in hybrid learning environments (Boland, Cherry, & Dickson, 2023). Finally, eligible studies were systematically analyzed and synthesized using thematic coding to identify recurring patterns, dominant research themes, methodological trends, and conceptual relationships across the selected literature. This synthesis enabled the development of an integrated understanding of how artificial intelligence and predictive analytics contribute to personalized hybrid learning models (Saldaña, 2021).

Overall, this structured and stepwise procedure strengthens the reliability, transparency, and replicability of the review findings and aligns with contemporary standards for systematic literature reviews in educational and social science research, particularly in studies addressing emerging educational technologies (Petticrew & Roberts, 2022).

Instruments, and Data Collection Techniques

The primary data consisted of textual data obtained from selected journal articles. A literature review matrix was employed as the main research instrument to systematically record essential information from each article, including author(s), year of publication, research objectives, methodological approach, technological focus, and key findings. Data collection was conducted through document analysis by accessing and downloading full-text articles from the selected databases. Document analysis is considered an appropriate technique for qualitative synthesis in review studies, as it enables consistent data extraction and comparison across multiple sources.

Data Analysis Technique

Data analysis was conducted using thematic analysis to systematically synthesize findings from the selected studies included in the systematic literature review. The extracted data were organized and coded to identify recurring patterns, concepts, and categories related to artificial intelligence applications, predictive analytics techniques, personalization mechanisms, and hybrid learning implementation (Saldaña, 2021). The coding process involved iterative reading and comparison of the reviewed articles to capture both explicit findings and underlying conceptual relationships across studies. Through this process, initial codes were refined into broader analytical themes that reflected dominant research trends, methodological approaches, and pedagogical implications of AI-driven personalization in hybrid learning environments (Braun & Clarke, 2021).

The identified themes were subsequently interpreted in relation to the research objectives to generate synthesized insights and conceptual explanations concerning how artificial intelligence and predictive analytics support adaptive learning pathways and learner-centered instructional design. The identified themes were subsequently interpreted in relation to the research objectives to generate synthesized insights and conceptual explanations concerning how artificial intelligence and predictive analytics support adaptive learning pathways and learner-centered instructional design (Donthu et al., 2021). Thematic analysis was selected due to its analytical flexibility and its suitability for systematically examining qualitative data within systematic literature reviews, particularly in interdisciplinary fields such as educational technology and learning analytics. This approach allows researchers to move beyond descriptive summaries and to construct meaningful interpretations that contribute to theory development and evidence-based practice (Nowell et al., 2021).

Overall, this analytical process enhanced the credibility and rigor of the review by ensuring transparency in theme development and consistency in data interpretation. As a result, the study was able to produce robust, evidence-based conclusions and offer substantive implications for the advancement of educational science in the context of artificial intelligence–supported hybrid learning (Petticrew & Roberts, 2022).

To ensure that the study is conducted in a planned, systematic, and replicable manner, this research is designed using the Systematic Literature Review (SLR) approach as the primary method. This approach is selected because it enables the synthesis of robust scientific evidence through clearly defined stages, ranging from research design to results analysis.

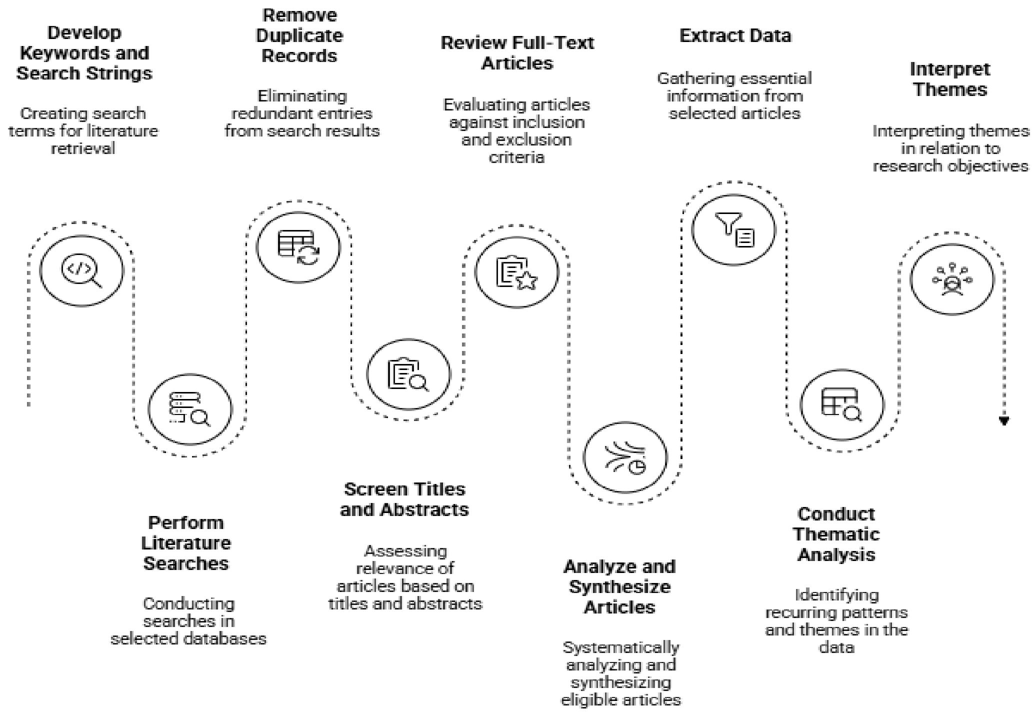

Figure 2 : Systematic Literature Review (SLR)

As illustrated in Figure 2, the SLR process begins with the development of the research design, which includes the formulation of research questions as well as the establishment of inclusion and exclusion criteria. This stage serves as a fundamental foundation for maintaining the focus and consistency of the study. Subsequently, a systematic literature search is conducted across relevant scientific databases using predefined keywords and search limitations. The retrieved articles then undergo a multi-stage selection process, starting with title and abstract screening followed by full-text review, to ensure that only relevant and high-quality studies are included. After the selection process, structured data extraction is performed to collect essential information aligned with the research objectives.

The final stage involves data analysis and synthesis, in which findings from the selected studies are critically examined and integrated to address the research questions. By following this systematic workflow, the SLR process not only strengthens the methodological validity of the study but also enhances the reliability and accuracy of the results obtained. Thus, from research design to data analysis, Figure 1 presents a systematic process that serves as a solid methodological foundation for the implementation of the Systematic Literature Review in this study.

RESULTS AND DISCUSSION

Grounded in the central focus of personalized hybrid learning enabled by artificial intelligence and predictive analytics, the Results and Discussion section presents a synthesis of findings derived from a systematic review of the literature. This synthesis goes beyond summarizing previous studies by highlighting recurring patterns, emerging trends, and conceptual interconnections that collectively shape an understanding of how intelligent technologies are employed to design adaptive learning experiences. To provide a coherent and structured overview of these findings, Figure 3 is presented as a visual representation that outlines the analytical direction and key results of the review, serving as a foundation for the more in-depth discussion developed in the subsequent sections.

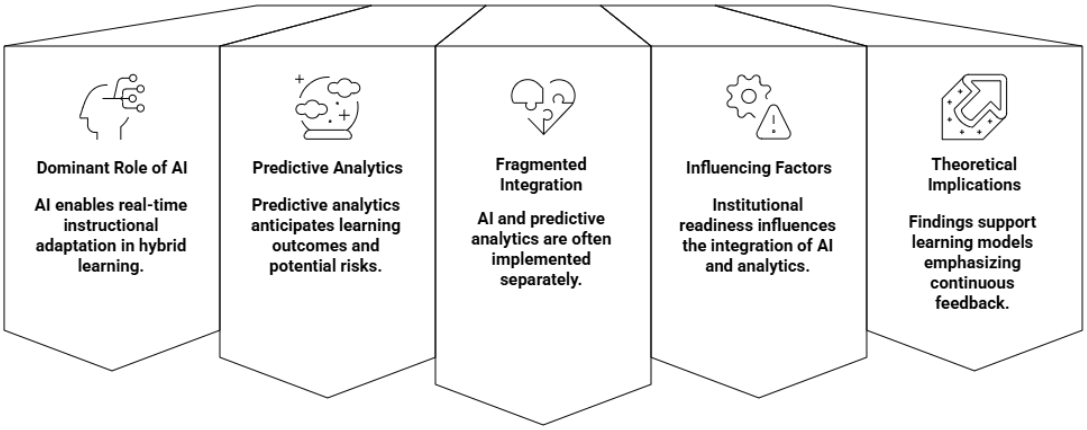

Figure 3 : Personalization Framework in Hybrid Learning

Dominant Role of Artificial Intelligence in Adaptive Personalization

The results indicate that artificial intelligence plays a dominant role in enabling adaptive personalization within hybrid learning environments. AI technologies are predominantly used to support real-time instructional adaptation, allowing learning systems to respond dynamically to variations in learner performance, preferences, and engagement patterns (Holmes et al., 2019). Through continuous data processing, AI-driven mechanisms facilitate personalized learning pathways that adjust content sequencing, difficulty levels, and feedback timing. This adaptability is particularly relevant in hybrid learning contexts, where learners experience fluctuating learning conditions between online and face-to-face modalities. Further analysis shows that the dominance of AI in personalization is closely related to its operational flexibility and scalability. AI systems can process large volumes of learner data with minimal delay, enabling immediate instructional responses that are difficult to achieve through conventional pedagogical approaches (Zawacki-Richter et al., 2019). This capability explains why AI is often positioned as the central engine of personalization in hybrid learning designs. However, reliance on AI-driven adaptation alone may lead to reactive personalization if not complemented by predictive insights that anticipate future learning needs.

Predictive Analytics as a Proactive Learning Support Mechanism

The findings reveal that predictive analytics primarily functions as a proactive tool for anticipating learning outcomes and potential learning risks. Predictive models analyze historical and real-time learner data to identify patterns associated with disengagement, low performance, or dropout risks (Akçapınar et al., 2019). By generating early warning indicators, predictive analytics enables educators and learning systems to intervene before learning challenges escalate. This proactive orientation distinguishes predictive analytics from descriptive analytics that merely report past learning outcomes. Additional examination suggests that the effectiveness of predictive analytics lies in its ability to support instructional foresight rather than immediate adaptation. Predictive insights provide strategic guidance for instructional planning, such as identifying learners who may require additional support or alternative learning pathways (Ifenthaler & Yau, 2020). Nevertheless, when predictive results are not directly linked to adaptive learning mechanisms, their practical impact remains limited. This finding underscores the need for tighter integration between prediction and personalization processes within hybrid learning environments.

Fragmented Integration of Artificial Intelligence and Predictive Analytics

Despite their complementary strengths, the results demonstrate that artificial intelligence and predictive analytics are frequently implemented as separate components. Many reviewed studies report parallel use of AI-driven personalization and predictive analytics without a unified operational framework connecting both technologies (Ifenthaler & Yau, 2020). This fragmented implementation results in learning systems that can adapt based on current learner behavior but lack the capacity to anticipate future learning challenges effectively. Consequently, personalization tends to occur after performance issues emerge rather than before they develop. Further analysis indicates that fragmentation is often rooted in conceptual and technical boundaries within system design. AI applications are typically embedded at the instructional interface level, while predictive analytics operates at the backend as an analytical function (Drachsler & Greller, 2020). This separation limits the translation of predictive insights into actionable instructional adaptations. As a result, hybrid learning systems fall short of achieving fully data-driven personalization that integrates both immediacy and anticipation.

Institutional and Technological Factors Influencing Limited Integration

The findings suggest that institutional readiness significantly influences the degree of integration between AI and predictive analytics. Studies highlight that limited technological infrastructure, insufficient data interoperability, and lack of institutional data governance frameworks hinder comprehensive system integration (Zawacki-Richter et al., 2019). These constraints force institutions to adopt partial implementations that emphasize technical feasibility and resource availability rather than pedagogical completeness, resulting in learning systems that only leverage a limited subset of artificial intelligence capabilities (Bond et al., 2021). As a result, advanced personalization strategies such as real-time adaptive learning paths, predictive intervention mechanisms, and fully individualized feedback remain underutilized in educational practice despite strong empirical evidence demonstrating their potential to improve learner performance and retention (Kovanović et al., 2022).

In addition to technological and infrastructural barriers, human and organizational factors, including limited staff expertise, resistance to pedagogical change, insufficient institutional support, and ethical concerns related to data governance, further explain the observed limitations in the large-scale adoption of AI-driven personalized and hybrid learning models (Selwyn, 2023). Educators and administrators often lack the analytical competencies required to interpret predictive data and translate it into instructional decisions (Viberg et al., 2020). This skills gap reinforces the tendency to rely on automated AI features while underusing predictive analytics outputs. Therefore, institutional capacity building emerges as a critical prerequisite for advancing integrated personalized hybrid learning systems.

Theoretical Implications for Data-Driven and Adaptive Learning Models

From a theoretical perspective, the findings support learning models that emphasize continuous feedback and adaptation. Data-driven learning theories argue that effective personalization depends on iterative interactions between learner data, instructional decisions, and learning outcomes (Drachsler & Greller, 2020). The prevalence of AI-driven adaptation observed in this review aligns with these theoretical assumptions, particularly in terms of responsiveness and learner-centered design. However, the limited integration of predictive analytics reveals a gap between theory and practice. While theoretical frameworks advocate anticipatory adaptation based on predictive insights, most empirical implementations remain reactive (Holmes et al., 2019). This discrepancy explains why personalized hybrid learning outcomes vary across contexts and highlights the need to operationalize predictive components more explicitly within adaptive learning models.

The novelty of this study lies in its integrative conceptualization of artificial intelligence and predictive analytics as a unified personalization ecosystem within hybrid learning environments. Rather than treating these technologies as independent solutions, this review synthesizes evidence showing that meaningful personalization emerges when real-time adaptation and predictive foresight function in a coordinated manner. This perspective advances existing literature by bridging fragmented research strands and offering a more holistic understanding of data-driven personalization in hybrid learning systems. The implications of this integrated perspective are both theoretical and practical. Theoretically, the findings contribute to the refinement of adaptive learning models by emphasizing the importance of linking predictive insights with adaptive instructional mechanisms. Practically, the results suggest that future hybrid learning designs should prioritize system interoperability, institutional readiness, and educator data literacy to maximize the pedagogical benefits of personalization. By aligning technological capabilities with instructional goals, hybrid learning systems can evolve into more responsive, equitable, and sustainable learning environments.

Overall, the findings demonstrate that artificial intelligence and predictive analytics play distinct yet complementary roles in supporting personalized hybrid learning, with AI predominantly enabling real-time adaptive personalization and predictive analytics contributing proactive instructional foresight. However, the synthesis of reviewed studies reveals that these technologies are often implemented in a fragmented manner due to conceptual separation in system design, institutional readiness constraints, and limited analytical capacity among educators. This fragmentation results in personalization practices that remain largely reactive rather than anticipatory, thereby constraining the full potential of data-driven hybrid learning environments. By integrating adaptive and predictive functions within a unified personalization ecosystem, hybrid learning systems can better align theoretical models of data-driven learning with practical implementation. Such integration offers a more coherent foundation for developing responsive, equitable, and sustainable hybrid learning designs that effectively address diverse learner needs through both immediate adaptation and forward-looking instructional support.

CONCLUSION

This study concludes that the integration of artificial intelligence and predictive analytics holds substantial potential for advancing personalized hybrid learning when implemented as a unified and data-driven ecosystem. The generalized findings indicate that artificial intelligence primarily supports real-time adaptive personalization, enabling instructional processes to respond dynamically to individual learner characteristics, while predictive analytics contributes anticipatory insights that facilitate proactive instructional decision-making. However, the review also reveals that current implementations remain largely fragmented, with limited alignment between adaptive mechanisms and predictive functions due to institutional, technological, and human capacity constraints.

These findings suggest that personalization in hybrid learning environments tends to remain reactive rather than anticipatory, which constrains its pedagogical effectiveness and consistency across contexts. Therefore, future research is recommended to move beyond isolated technological applications and focus on developing integrated frameworks that systematically connect predictive insights with adaptive instructional strategies. In addition, further empirical studies are needed to examine institutional readiness, data governance, and educator data literacy as critical enablers of sustainable data-driven personalization. By addressing these dimensions, subsequent research and practice can contribute to the development of more responsive, equitable, and evidence-based hybrid learning systems.

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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