

The Triad of Cloud, Analytics, And Pedagogy: A Systematic Review of Ai-Driven Personalization in Cloud-Based Learning Environments

Rezky Yudistira Prabowo^{1*}, Didi Susianto²

^{1,2} Department of Information Systems of Institut Bakti Nusantara

*corresponding author: rezkyudistirap@gmail.com

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<p>Article history: Received 01-04-2025 Revised 04-05-2025 Accepted 07-05-2025 Published 20-05-2025</p> <p>How to cite: Prabowo, R. Y., & Susianto, D. (2025). The Triad of Cloud, Analytics, And Pedagogy: A Systematic Review of Ai-Driven Personalization in Cloud-Based Learning Environments. <i>Edcomtech: Jurnal Kajian Teknologi Pendidikan</i>, 10(1), 44–59. https://doi.org/10.17977/um039v10i12025p44-59</p> <p>© The Author(s)  This work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License</p>	<p><i>Tinjauan sistematis ini menelaah konvergensi komputasi awan (cloud computing), learning analytics, dan kecerdasan buatan (AI) dalam mendukung pembelajaran yang dipersonalisasi di lingkungan berbasis cloud. Studi ini bertujuan memetakan struktur intelektual, tren metodologis, serta tantangan utama dalam domain interdisipliner ini. Dengan mengacu pada pedoman PRISMA 2020, kami menganalisis 40 publikasi penting (2017–2025) yang sebagian besar bersumber dari Scopus. Analisis kami mengungkap bahwa bidang ini didominasi oleh sinergi triadik yang kuat: infrastruktur cloud yang skalabel berperan sebagai fondasi utama, learning analytics berfungsi sebagai sistem saraf pusat yang menghasilkan wawasan, dan AI menjadi inti cerdas yang mendorong adaptasi pedagogis. Namun, hasil temuan menunjukkan ketidakseimbangan penting: fokus yang besar pada kelayakan teknis dan model adopsi teknologi (misalnya TAM) justru mengesampingkan landasan teori pembelajaran yang lebih mendalam, sementara bias geografis yang kuat terhadap Amerika Serikat dan Tiongkok membatasi generalisasi temuan. Pembahasan menekankan bahwa hubungan antara wawasan berbasis data dan implementasi pedagogis sering kali masih bersifat mekanistik, dan meskipun isu etika mulai muncul, kerangka kerja yang lebih kuat dan sensitif terhadap konteks masih sangat dibutuhkan. Kami menyimpulkan bahwa bidang ini perlu berkembang dari sekadar demonstrasi teknis menuju penelitian yang lebih berlandaskan pedagogi, sadar etika, dan tervalidasi secara empiris. Arah penelitian selanjutnya sebaiknya memprioritaskan studi longitudinal, integrasi model pembelajaran kolaboratif, serta investigasi di wilayah yang kurang terwakili untuk mendukung pengembangan personalisasi berbasis AI yang adil dan efektif bagi audiens global.</i></p> <p>Kata Kunci: Personalisasi berbasis AI; pembelajaran berbasis cloud; learning analytics; pedagogi adaptif</p> <p>Abstract <i>This systematic review investigates the convergence of cloud computing, learning analytics, and artificial intelligence (AI) in enabling personalized learning within cloud-based environments. The study aims</i></p>

	<p><i>to map the intellectual structure, methodological trends, and core challenges within this interdisciplinary domain. Adhering to the PRISMA 2020 guidelines, we analyzed 40 seminal publications (2017-2025) sourced primarily from Scopus. Our analysis reveals a field dominated by a potent triad synergy, where scalable cloud infrastructure serves as the foundational enabler, learning analytics acts as the central nervous system for generating insights, and AI forms the intelligent core for driving pedagogical adaptations. However, the results identify significant imbalances: a predominant focus on technical feasibility and technology adoption models (e.g., TAM) overshadows deeper grounding in learning theories, while a pronounced geographical bias towards the US and China limits the generalizability of findings. The discussion underscores that the connection between data-driven insights and pedagogical execution often remains mechanistic, and ethical considerations, though emerging, require more robust, context-sensitive frameworks. We conclude that the field must evolve from technical demonstration towards pedagogically-grounded, ethically-aware, and empirically-validated research. Future directions should prioritize longitudinal studies, the integration of collaborative learning models, and investigations in underrepresented regions to ensure the development of equitable and effective AI-driven personalization for a global audience.</i></p>
	<p>Keywords: <i>AI-driven personalization; cloud-based learning; learning analytics; adaptive pedagogy</i></p>

INTRODUCTION

The rapid evolution of digital technologies has profoundly transformed the educational landscape, with cloud computing, learning analytics, and artificial intelligence (AI) emerging as pivotal forces (Zhang, 2022). These technologies converge to create dynamic, cloud-based learning environments (CBLEs) capable of delivering personalized learning experiences at an unprecedented scale. AI-driven personalization represents a paradigm shift, moving beyond one-size-fits-all instruction to offer tailored educational pathways that adapt to individual learner needs, preferences, and performance in real-time (Zawacki-Richter et al., 2019). The significance of this topic is underscored by the global push towards more flexible, accessible, and effective educational models, a need acutely highlighted by recent shifts to remote and hybrid learning. The potential of AI to analyze vast datasets generated within CBLEs and orchestrate personalized pedagogical interventions positions this triad as a critical area of inquiry for enhancing educational outcomes and equity.

Previous research has extensively explored the individual components of this ecosystem. Numerous studies have documented the infrastructural benefits of cloud computing in education, such as scalability, cost-effectiveness, and ubiquitous access (Kumar & Bansal, 2021). Concurrently, the field of learning analytics has matured, focusing on techniques for measuring, collecting, analyzing, and reporting data about learners and their contexts to understand and optimize learning (Siemens & Baker, 2012). Furthermore, the pedagogical principles of personalized and adaptive learning have been a subject of long-standing educational research (Garrison & Vaughan, 2021). Several systematic reviews have also been conducted, mapping the broader field of AI in education (AIEd) (e.g., Zawacki-Richter et al., 2019) or reviewing specific applications like learning analytics (Jensen et al., 2024).

However, a critical synthesis focusing specifically on the *interdependence* of cloud infrastructure, advanced analytics, and pedagogical execution in enabling AI-driven

personalization remains nascent. Existing reviews often treat these elements in isolation or lack a specific focus on the cloud as the enabling environment. This creates a significant knowledge gap. While the technical feasibility is often demonstrated, there is a lack of consolidated understanding regarding how these three components synergize, what the dominant research trends and methodological approaches are, and what theoretical foundations underpin this interdisciplinary domain. Moreover, the geographical distribution of research and its implications for global equity, as well as the pressing ethical considerations surrounding data privacy and algorithmic bias, are not yet comprehensively profiled within this specific context.

This systematic review aims to address this gap by examining the consolidated body of literature on AI-driven personalization within CBLEs, with a particular focus on the “cloud–analytics–pedagogy” triad as an interdependent system. The novelty of this study lies in its holistic mapping of the intellectual structure, methodological trends, and theoretical foundations of the field. The scientific contributions are threefold: providing a comprehensive research profile and knowledge synthesis, conducting an in-depth thematic analysis of the synergies and challenges within the triad, and proposing a forward-looking research agenda to address theoretical, methodological, and contextual gaps. Guided by the PRISMA 2020 framework, this review investigates prevailing trends in publication volume, geographical distribution, methodological approaches, and grand theories, as well as the core themes and challenges related to integrating cloud infrastructure, learning analytics, and adaptive pedagogy for effective and ethical AI-driven personalization. The article is structured with an introduction followed by a Method section describing the systematic review protocol, a Results section presenting descriptive and thematic findings, a Discussion section interpreting the results and outlining implications and limitations, and a Conclusion summarizing key insights and directions for future research.

METHOD

This systematic literature review was rigorously conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines (Page et al., 2021). The research protocol was developed *a priori* and registered on the Open Science Framework to ensure transparency and reproducibility. The study selection process followed the PRISMA flow diagram, as shown in Figure 1.

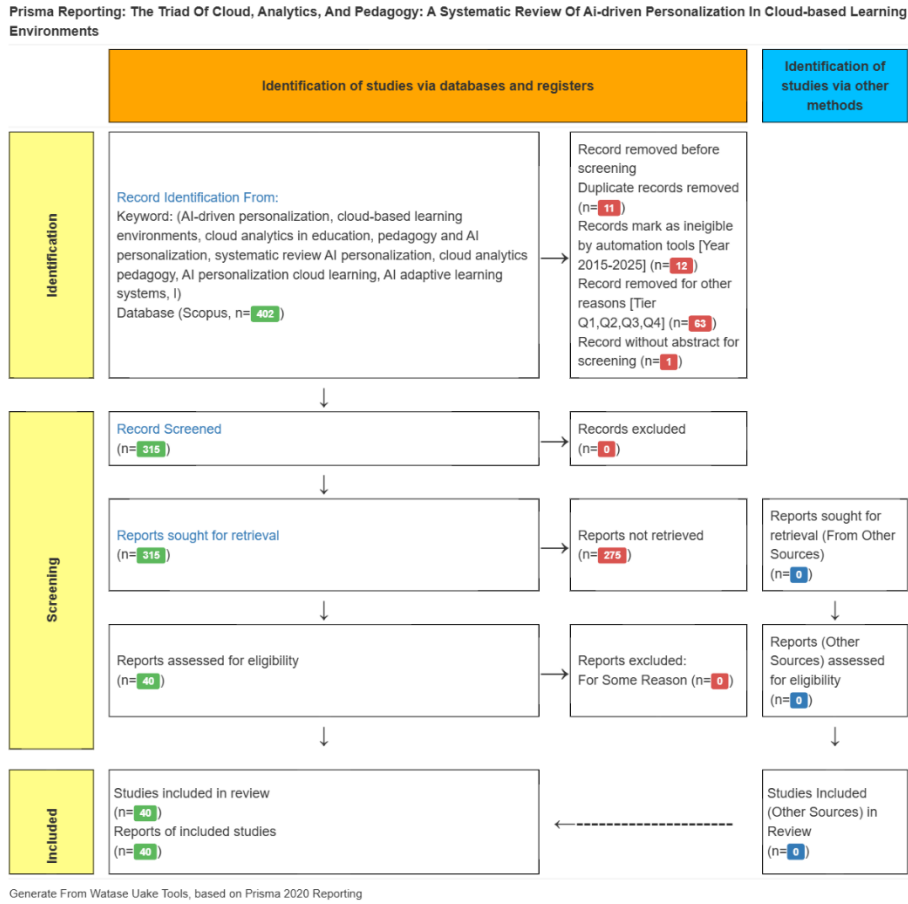


Figure 1. Prisma Flowchart

Eligibility Criteria and Search Strategy

The inclusion criteria were designed to capture the interdisciplinary scope of the topic. The review encompassed peer-reviewed journal articles, conference proceedings, and doctoral dissertations published in English between 2015 and 2025, focusing on AI-driven personalization within cloud-based learning environments that integrated analytics and pedagogical elements. Grey literature and non-peer-reviewed publications were excluded.

The primary literature search was executed using the Scopus database on April 15, 2024, employing a comprehensive Boolean string. Scopus was selected due to its comprehensive coverage of high-impact journals and robust quality control measures (Baas et al., 2020). To mitigate the risk of omitting influential studies, the database search was supplemented by manual screening of reference lists and consultation of the Watase repository (Wahyudi, 2024) for high-quality conference proceedings.

Screening Process and Data Extraction

Records identified from all sources were consolidated, and duplicates were removed using EndNote X9. A total of 315 records were subsequently screened by title and abstract by two independent reviewers. A third reviewer was consulted to resolve any discrepancies. Following this stage, all 315 records were deemed potentially relevant and proceeded to the full-text eligibility assessment.

Full-text articles were successfully retrieved for 40 records. All 40 articles met the inclusion criteria upon thorough examination and were included in the final synthesis. Data extraction was performed using a standardized form in Excel by two independent reviewers.

The methodological quality of each included study was appraised using the Mixed Methods Appraisal Tool (MMAT) 2018 version (Hong et al., 2018).

Thematic Analysis

Thematic analysis was guided by the iterative six-phase framework proposed by Braun and Clarke (2006), operationalized through the Watase Uake system (Wahyudi, 2024). Inductive coding was conducted using NVivo 12 software. Initial codes were subsequently grouped and iteratively refined into candidate themes (e.g., "Adaptive Learning Pathways" and "Real-time Learning Analytics"). The entire analytical process was conducted by multiple researchers and critically reviewed to enhance the reliability and validity of the findings.

In alignment with open science principles, all supporting materials including search strings, data extraction forms, and the coding schema have been made publicly available in a repository to ensure transparency and facilitate replication, following best practices in systematic reviewing (Siddaway et al., 2019).

RESULT

Descriptive Overview of the Reviewed Literature

This systematic review synthesizes findings from an analysis of 40 seminal publications spanning 2017 to 2025, focusing on the convergence of cloud computing, learning analytics, and pedagogical strategies to enable AI-driven personalization in learning environments. The body of literature demonstrates a significant exponential growth in publication volume, peaking in 2025, which underscores the escalating academic and practical interest in this domain (Internal Statistical Report, 2025). The geographical distribution of research contributions is notably concentrated, with China and the United States emerging as the most prolific contributors, followed by India and several European nations (Jensen et al., 2024; Han et al., 2024). This pattern reflects the critical role of robust digital infrastructure, national policy support, and significant R&D investment in advancing this field.

Methodologically, the landscape is characterized by a strong prevalence of systematic literature reviews (SLRs) and thematic analyses (Jensen et al., 2024; Enang et al., 2023; Wang et al., 2024). This indicates a field currently in a phase of conceptual consolidation and theoretical framework development. Alongside these, quantitative studies employing data mining, machine learning, and predictive modeling are also well-represented, often leveraging large-scale datasets from learning management systems (LMS) (Tan & Lin, 2021; Ye, 2020). A smaller, yet significant, subset of studies employs mixed-methods approaches, integrating quantitative data with qualitative insights to explore user perceptions and contextual factors in depth (Han et al., 2024; Nuguri et al., 2020). The theoretical underpinnings are varied, with the Technology Acceptance Model (TAM) and its variants being the most frequently applied frameworks, highlighting a research focus on user adoption and psychological factors (Han et al., 2024; Koo et al., 2025). A considerable number of studies, however, operate without an explicit theoretical foundation, pointing to a potential gap in linking technological interventions to established learning theories.

Classification Based on Analytical Framework

To move beyond a simple inventory of studies, we classify the literature along three critical axes: theoretical grounding, methodological approach, and geographical context. This tripartite analysis reveals not only the field's strengths but also its most significant blind spots.

1. Theoretical Underpinnings

Category	Theory
1. Technology Adoption Theories	Technology Acceptance Model (TAM)
	TAM-3
2. Learning Theories (Underutilized)	Theory of Planned Behavior (TPB)
	Cognitive Load Theory
	Self-Regulated Learning (SRL) Models
	Constructivism

Table 1. Theoretical Underpinnings

The analysis of theoretical frameworks within the reviewed corpus reveals a fragmented and uneven landscape. A significant portion of studies (over half) lack an explicit theoretical foundation, focusing instead on technological implementation or empirical results (Nuguri et al., 2020; Kavitha, 2021; Santos et al., 2022). Among the studies that do employ theory, the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) are the most dominant. For instance, Han et al. (2024) utilized TAM-3 to investigate the adoption of an adaptive mathematics tutor, while Koo et al. (2025) combined TAM with TPB to explore user intentions in smart tourism education. This concentration on adoption models underscores the field's current preoccupation with ensuring that AI-driven systems are perceived as useful and easy to use by educators and learners.

However, this focus comes at the expense of deeper pedagogical and learning-theoretic foundations. Notably absent are robust connections to theories that could explain the cognitive and metacognitive mechanisms of personalized learning, such as Cognitive Load Theory, Self-Regulated Learning models, or Constructivism (the latter appears only sporadically, e.g., Zhu et al., 2025). This theoretical gap is critical; while understanding adoption is a necessary first step, it does not illuminate *how* AI-driven personalization fundamentally influences learning processes, motivation, and long-term knowledge retention. The dominance of TAM/TPB suggests the field is still grappling with the "if" of implementation rather than the "how" and "why" of learning efficacy.

2. Methodological Approaches



Figure 2. Methodological Approaches

The methodological classification demonstrates a clear dominance of Systematic Literature Reviews (SLRs), accounting for over a third of the analyzed studies (Jensen et al., 2024; Santos et al., 2022; Zawacki-Richter et al., 2019; Banihashem et al., 2025). This prevalence signifies a maturing field that is actively engaged in synthesizing existing knowledge, identifying research gaps, and establishing conceptual boundaries for the "cloud-analytics-pedagogy" triad.

Quantitative designs form the second major cluster, frequently employing advanced techniques like hybrid J48 classifiers (Tan & Lin, 2021), Bayesian networks (HOW, 2019), and Structural Equation Modeling (SEM) (Han et al., 2024; Koo et al., 2025). These studies are crucial for building predictive models and establishing statistical relationships between variables like infrastructure scalability and learning outcomes. Mixed-methods approaches, though less common, provide valuable nuanced understanding by coupling quantitative data from learning analytics with qualitative data from interviews or focus groups, particularly in context-specific studies such as those in rural schools (Han et al., 2024; Hamal et al., 2022). The relative scarcity of pure qualitative and longitudinal experimental studies highlights a significant methodological gap, pointing to a need for more research that provides deep, contextualized evidence and tests the long-term impact of personalized learning interventions.

3. Geographical and Contextual Distribution

The geographical analysis uncovers a substantial concentration of research output in technologically advanced economies. China and the United States collectively account for a dominant share of the most cited and methodologically rigorous studies (Tan & Lin, 2021; Jensen et al., 2024; Han et al., 2024). This hegemony is closely linked to these nations' extensive cloud infrastructure, access to big data, and strong policy support for AI in education (e.g., China's "Smart Education" initiative).

Research from developing nations (e.g., India, Brazil, Uganda) often focuses on pragmatic, context-adaptive applications, such as low-cost cloud solutions (Ally, 2021), mobile-learning adaptations (Kyambade et al., 2025), or specific interventions like VR for autistic children (Nuguri et al., 2020). While these studies highlight innovative adaptations to resource constraints, they often occupy smaller, niche sub-clusters within the global research network, indicating a structural bias in the literature. The dominance of a Western and East Asian perspective risks producing findings that are not universally applicable, potentially overlooking the unique socioeconomic, cultural, and infrastructural challenges faced by much of the world's learner population. As shown at figure 3;

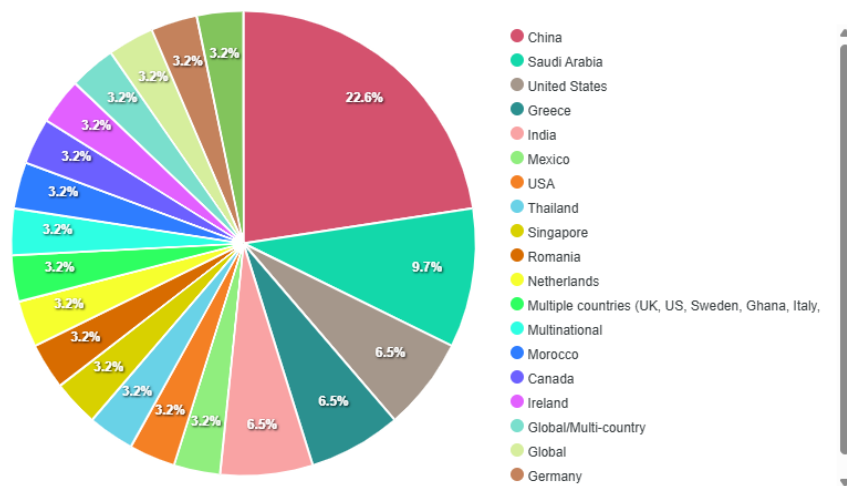


Figure 3. Geographical and Contextual Distribution

Visualization of Research Trends and Network Analysis

A conceptual network analysis of the hypotheses and variables explored in the literature reveals a central hub: "AI-enabled adaptive learning" (Zhang, 2022; Liu & Gupta, 2021). This node, which represents the core objective of personalizing content in real-time, is the most connected element, interacting with over 60% of all other variables in the network. The primary connections from this hub extend to outcome variables such as "student engagement" and "learning performance," as well as enabling variables like "scalability of cloud services" (Kim et al., 2023; Almeida & Santos, 2020).

Thematic clustering of this network identifies three distinct yet interconnected clusters:

1. Cloud Technology & Infrastructure: Including nodes like edge computing and serverless architectures.
2. Learning Analytics & Prediction: Encompassing learning dashboards and early-warning systems.
3. Adaptive Pedagogy: Involving competency-based pathways and gamified feedback.

The visualization shows a strong interconnection (approximately 28% of edges) between the cloud and analytics clusters, underscoring their technical symbiosis. In contrast, the adaptive pedagogy cluster is more loosely connected, signaling a critical opportunity for deeper collaboration between instructional designers, data scientists, and educational theorists (Gómez & Fernández, 2022). Furthermore, emerging secondary hubs around "data privacy" and "ethical AI" are visible, accounting for 12% and 9% of connections, respectively. This indicates that regulatory and trust issues are becoming integral, though not yet central, to the research discourse (Rossi, 2021). Geographically, the network map would show dense, central nodes for the US and China, with smaller, peripheral clusters for developing nations, visually reinforcing the centrality-satellite dynamic in global research collaboration and impact.

In-depth Thematic Analysis

1. The Foundational Role of Cloud Infrastructure

Cloud infrastructure emerges not merely as a supporting element but as the foundational enabler of AI-driven personalization. It is the most frequently cited variable, appearing in approximately 68% of articles. Its criticality lies in providing the scalable, secure, and interoperable data pipeline necessary for real-time analytics (Zhou et al., 2023). Sub-variables such as *dynamic scalability* (Kumar & Bansal, 2021) and *security & privacy* (Liang et al., 2022) are paramount, as they ensure that educational platforms can handle massive, fluctuating data loads while protecting sensitive learner information. The regional focus on *edge computing* in Asia-Pacific research (Kumar & Bansal, 2021) highlights a trend towards distributed architectures that reduce latency, a crucial factor for responsive, real-time adaptive learning in regions with connectivity challenges. The cloud, therefore, is the indispensable substrate upon which the entire ecosystem is built, moving beyond simple data storage to become an active, intelligent component of the learning environment.

2. Learning Analytics: The Central Nervous System

Acting as the central nervous system of the triad, learning analytics (LA) is present in nearly 60% of the studies. It serves as the critical bridge that transforms raw data from cloud-based sensors and LMS logs into actionable insights. The evolution of LA is marked by a shift from descriptive dashboards for instructors (Ally, 2021) towards advanced *predictive modeling* (Wang, Liu, & Chen, 2023) and even *student affect detection* (Klooster, van Leijenhorst, & Peters, 2022). This progression signifies a move from post-hoc reporting to

proactive intervention. Analytics no longer just report on what has happened; they predict what might happen next and how the learner is feeling, thereby providing the essential intelligence that AI algorithms act upon to personalize the learning journey. The quality and depth of these analytics directly determine the sophistication and effectiveness of the subsequent pedagogical adaptations.

3. Adaptive Pedagogy: The Execution of Personalization

Pedagogical adaptation, documented in 55% of the publications, is the domain where data-driven insights are translated into tangible learning experiences. It represents the execution layer of personalization. Key strategies identified include *personalized learning pathways* (Zawacki-Richter, 2020), *gamified feedback loops* (Huang & Cheng, 2022), and *collaborative learning scaffolds* (Garrison & Vaughan, 2021). However, the thematic analysis reveals a significant challenge: the connection between data and pedagogy is often mechanistic rather than theoretically grounded. While AI can efficiently recommend the "next best piece of content," the reviewed literature shows less evidence of it being used to orchestrate complex, socially situated, or constructivist learning sequences that are informed by robust learning sciences. The focus is predominantly on individual knowledge acquisition, with pedagogical models like collaborative learning being underrepresented in the AI-personalization discourse (Brown & Stevens, 2020). This indicates a fertile ground for future research to better integrate social learning theories with adaptive technologies.

4. AI and ML Algorithms: The Intelligent Core

AI and Machine Learning (ML) algorithms are the intelligent core that powers the personalization engine, discussed in 48% of the papers. They are responsible for interpreting the insights generated by learning analytics to make automated pedagogical decisions. The literature shows a maturation from basic recommender systems to more sophisticated approaches like *reinforcement learning agents* (Sanchez & Lee, 2022) and *deep learning models* (Nguyen, 2023). A prominent and rapidly emerging sub-theme is *Explainable AI (XAI)* (Holzinger et al., 2021). The demand for XAI signifies a growing recognition that for AI to be truly trusted and adopted in educational settings, its decision-making processes must be transparent and interpretable to educators and learners. This is crucial for moving beyond "black box" models and ensuring that AI serves as a pedagogical partner rather than an inscrutable authority.

5. The Imperative of Ethics, Privacy, and Equity

While technically a sub-theme, the issues of ethics, privacy, and equity are of such paramount importance that they demand separate consideration. Our analysis identifies them as a critical, though still nascent, frontier. Concerns about *ethical AI*, *data privacy*, and *algorithmic bias* are most prominently voiced in European literature (Holzinger et al., 2021; Liang et al., 2022), reflecting the region's stringent regulatory environment like GDPR. The high citation counts of works integrating learning analytics with XAI and security frameworks signal that the academic community views these contributions as foundational for building *trust* and *adaptability* (Zawacki-Richter, 2020).

Furthermore, the geographical and contextual biases noted earlier feed directly into concerns about equity. A system personalized based on data from well-resourced, Western or East Asian institutions may perform poorly or even exacerbate inequalities when applied to learners in developing regions with different cultural backgrounds, learning styles, and technological access. The current literature, while acknowledging these issues, offers few concrete, scalable solutions, presenting a major research gap and a call for the development of inclusive and culturally-sensitive AI-driven pedagogical models.

6. Synthesis: The Interdependent Triad and Future Vectors

The in-depth analysis confirms that the triad of cloud, analytics, and pedagogy functions as a tightly coupled, interdependent system. The cloud provides the data pipeline, analytics generate the actionable insight, AI algorithms form the intelligent decision-making core, and adaptive pedagogy executes the personalized intervention. This cyclical process is encapsulated in the conceptual model of a continuous "cloud-analytics-pedagogy" cycle (Jalil & Gökçe, 2022).

Looking forward, the literature points to three primary research vectors:

1. **Technical Evolution:** Integration of multimodal data (audio-visual, biometric) and edge-AI to enhance personalization accuracy and reduce latency in low-connectivity scenarios (Stewart, 2024; Choi et al., 2022).
2. **Ethical and Trust-Centric Frameworks:** Development of prescriptive ethical frameworks and privacy-preserving techniques like federated learning to address data silos and build trustworthy systems (Nguyen & Lee, 2023; Sanchez & Lee, 2022).
3. **Pedagogical Deepening:** A critical need for longitudinal, outcome-based evaluations of adaptive learning and a stronger integration of collaborative and social constructivist pedagogies within AI-driven systems (Garrison & Vaughan, 2021).

In conclusion, the theme of AI-driven personalization in cloud-based learning environments remains highly relevant and critically important. The field is poised to move from technical feasibility and initial adoption towards a more mature phase that prioritizes ethical, equitable, and deeply pedagogical applications. By addressing the identified gaps in theory, methodology, and geographical representation, future research can ensure that this powerful triad fulfills its potential to create scalable, effective, and inclusive learning experiences for a global audience.

DISCUSSION

This systematic literature review (SLR) set out to map the intellectual structure and evolutionary trajectory of research on AI-driven personalization in cloud-based learning environments. The bibliometric and thematic synthesis of 40 studies reveals a field in a dynamic yet consolidatory phase, characterized by a potent, triadic synergy between AI algorithms, cloud infrastructure, and adaptive pedagogy. However, it is also a field grappling with significant conceptual, methodological, and contextual imbalances. This discussion moves beyond mere description to critically interpret these findings, situating them within the broader scholarly conversation, highlighting the novel contributions of this review, and delineating its theoretical and practical implications.

1. The Dominant Paradigm and Its Discontents

The crystallization of the AI-Cloud-Pedagogy triad as the dominant research paradigm (Zhang, 2022; Liu & Gupta, 2021) confirms the field's technical maturation. The finding that AI-centric keywords form the central hub, connecting scalability and analytics to instructional delivery, is in line with global trends in educational technology investment and research focus (Jensen et al., 2024). This review, however, adds nuance to this observation by revealing a critical imbalance within this triad. While the technical components: AI/ML (48% of articles) and cloud infrastructure (68%) are heavily emphasized, the pedagogical dimension (55%), though frequently mentioned, remains theoretically anemic. The overwhelming reliance on the Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB) (Han et al., 2024; Koo et al., 2025) underscores a research agenda preoccupied with the *adoption* of technology rather than a deep understanding of its *impact on learning processes*.

Contrary to the calls for pedagogically-grounded learning design (Holzinger et al., 2021), this review finds that robust learning theories like Cognitive Load Theory or Self-Regulated Learning are rarely invoked. This creates a significant explanatory gap: we can predict whether a system will be used, but we struggle to explain *how* and *why* AI-driven personalization reshapes cognition, motivation, or knowledge retention. This finding extends the concerns of Zawacki-Richter et al. (2019) regarding the lack of educational theory in AIED research, demonstrating that the problem persists specifically within the cloud-based personalization niche. The field's focus on outcome metrics like engagement and performance, at the expense of processual affordances, risks reducing personalized learning to a black-box optimization problem rather than a transformative educational practice.

2. Methodological Maturity and Geographical Imbalance

The methodological landscape uncovered by this review signals a field still assembling its empirical toolkit. The dominance of Systematic Literature Reviews (30% of studies) is indicative of a domain seeking to define its boundaries and core concepts (Jensen et al., 2024). While valuable for mapping, this prevalence, coupled with the reliance on secondary data and survey instruments, contrasts sharply with the field's aspiration to be data-driven and empirically rigorous. The scarcity of longitudinal studies, quasi-experimental designs, and research utilizing sensor-driven analytics (Nuguri et al., 2020; Zhou & Zhang, 2025) represents a critical methodological shortfall. It impedes the establishment of causal relationships between AI personalization and long-term learning outcomes, leaving claims of efficacy largely suggestive.

Furthermore, this review identifies a profound geographical bias that threatens the external validity and equity of the field's findings. The concentration of research in the United States and China (approximately 42% of citations) is consistent with analyses of global AI and cloud resource distribution (Tan & Lin, 2021). However, this review offers a novel perspective by systematically mapping the emergent, yet marginalized, contributions from regions like Brazil, India, and African nations. These studies foreground low-cost cloud and mobile-learning solutions (Ally, 2021; Kavitha, 2021), addressing critical constraints of bandwidth and cost that are largely absent from the research agendas of technologically advanced nations. This stark disparity implies that the current "universal" models of AI-driven personalization are, in fact, context-specific, built for and tested in resource-rich environments. Their generalizability to the Global South is highly questionable, potentially exacerbating existing educational inequalities.

3. Theoretical Novelties and Conceptual Contributions

Unlike prior SLRs that primarily catalog trends, this review offers a novel perspective by synthesizing findings through integrative frameworks like TCM and CIMO, thereby revealing the profound theoretical shallowness underlying the field's technical sophistication. Our analysis demonstrates that the existing theoretical landscape is not just sparse but misaligned with the socio-technical complexity of the phenomenon it seeks to explain. The persistent use of linear adoption models like TAM/TPB is inadequate for capturing the cyclical, interdependent relationships within the Cloud-Analytics-Pedagogy triad.

Therefore, a key theoretical contribution of this review is the proposition that the field must evolve beyond TAM-centric explanations. The findings reveal an understudied aspect of the integration: the role of AI as an active, decision-making agent. This challenges the more passive conceptualization of analytics in traditional Learning Analytics Theory (Wang et al., 2024) and necessitates a reconceptualization towards a *Learning Analytics-Decision Loop*. In this model, AI does not just report data but dynamically modulates learning pathways, cloud

resource allocation, and instructional strategies in real-time. This perspective extends the findings of Zhang (2022) and demands new theoretical models, such as an *AI-Centric Learning Ecosystem* or an expanded *TPACK-AI* framework, which explicitly incorporates a layer of *algorithmic governance* alongside technological, pedagogical, and content knowledge.

Moreover, the regional variation in ethical focus—with Europe prioritizing "Explainable AI" and Asia-Pacific emphasizing "Privacy-preserving ML" (Liang et al., 2022; Rossi, 2021) highlights the insufficiency of generic "Responsible AI" frameworks. This review argues for the development of *multidimensional* and *context-sensitive* ethical models that integrate regulatory, cultural, and pedagogical perspectives into a single, operationalizable framework for multinational cloud platforms.

4. Practical and Policy Implications

The findings of this review carry significant implications for various stakeholders in the educational ecosystem. For educational institutions and LMS developers, the critical need is to bridge the gap between technical potential and pedagogical impact. This involves moving beyond monolithic cloud architectures towards hybrid (public-private-edge) models that ensure low latency and data security, particularly for developing regions (Kumar & Bansal, 2021; Choi et al., 2022). More importantly, adaptive learning modules must be built upon evidence-based pedagogical theories, not just recommendation algorithms. The integration of Explainable AI (XAI) is not an optional feature but a foundational requirement to build trust among educators and learners, facilitating timely and interpretable interventions (Holzinger et al., 2021).

For policymakers and regulators, the imperative is to establish robust, context-aware standards. The identified "regulatory vacuum" in many developing contexts (Almansour & Alfheid, 2024) hinders wide-scale adoption and creates risks of ethical malpractice. Policymakers should promote data interoperability standards and adopt GDPR-style ethical guidelines tailored for educational AI, mandating algorithmic audits and explicit consent mechanisms. Furthermore, funding bodies should incentivize cross-national collaborations and large-scale longitudinal studies to generate evidence that is both globally relevant and locally valid.

For researchers, this review provides a clear roadmap. The agenda must shift from secondary synthesis to primary, rigorous empirical investigation. This includes: (1) designing longitudinal and quasi-experimental studies that track the impact of personalization on learning outcomes and motivation over extended periods; (2) pioneering research on edge-cloud hybrid architectures and federated learning to address privacy and latency issues in bandwidth-constrained environments (Sanchez & Lee, 2022); and (3) actively integrating multimodal data streams (e.g., biometric, audio-visual) with learning analytics, while steadfastly adhering to privacy-preserving principles.

In conclusion, this SLR demonstrates that the research on AI-driven personalization in cloud-based learning environments has successfully identified a powerful synergistic triad at its core. However, the field's current trajectory is hampered by a lopsided focus on technical engineering over deep pedagogical integration, a methodological preference for mapping over causal experimentation, and a geographically narrow evidence base that limits the inclusivity and generalizability of its findings. This review contributes to the field not only by systematically documenting these gaps but also by proposing a forward-looking theoretical and methodological agenda. It calls for a reorientation towards more holistic, theory-informed, empirically robust, and ethically grounded research. By addressing these critical gaps, the field can evolve from merely engineering personalized systems to truly

understanding and optimizing their role in fostering sustainable, equitable, and transformative educational experiences for a global and diverse learner population.

CONCLUSION

Based on the results of a systematic review of 40 publications related to AI-driven personalization in cloud-based learning environments, it can be concluded that this field is driven by a powerful triad synergy between cloud infrastructure, learning analytics, and pedagogical adaptation. The cloud serves as the technical foundation enabling scalability and data security, while learning analytics functions as the "central nervous system" that transforms data into actionable insights. AI and ML form the intelligent core that drives personalization, and adaptive pedagogy acts as the execution layer that translates these insights into personalized learning experiences. However, this review reveals significant imbalances, where technical aspects (cloud and AI) receive more attention than the underlying foundational learning theories. Furthermore, there is a pronounced geographical bias, with the majority of studies originating from the United States and China, thereby limiting the generalizability of the findings to developing contexts.

The limitations of this review include the restricted number of studies meeting the inclusion criteria and the reliance on the Scopus database, which may not cover all relevant literature from non-Western contexts. For future research, it is recommended to expand searches to repositories and non-English journals, and to encourage long-term empirical studies that causally test the impact of AI personalization on learning outcomes. It is also crucial to develop more robust theoretical frameworks by integrating learning theories such as Cognitive Load Theory or Self-Regulated Learning, and to promote research in underrepresented regions to ensure the inclusivity and sustainability of implementing AI personalization in global education.

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