Smart Learning Environments

REVIEW

Open Access

Redefining personalized learning in the artificial intelligence era: an updated systematic review from 2019 to 2025

Fatima Khalifeh[1*], Raúl Santiago[2] and Ramon Palau[3]

*Correspondence:
fatima.khalifeh@liu.edu.lb

[1] School of Education, Lebanese International University, Beirut, Lebanon
[2] Department of Educational Sciences, Universidad de La Rioja, 26006 Logroño, Spain
[3] Department of Pedagogy, Universidad Rovira I Virgili, 43003 Tarragona, Spain

Abstract

The integration of artificial intelligence (AI) in education is prompting a reevaluation of personalized learning terminology and its impact on teaching practices and learner engagement. Personalized learning (PL) involves various instructional strategies tailored to individual student needs and interests, utilizing data and technology to boost engagement and success. The evolving landscape requires a clear understanding of how AI can support personalized learning, distinguishing it from traditional methods. The variability in PL terminology reflects diverse interpretations of AI technologies in education, necessitating a common framework to clarify definitions and practices. This document presents an overview of the latest research literature on personalized learning, highlighting how technology is transforming the framework and effectiveness of individualized learning experiences. By analyzing reputable articles from 6 databases, the review seeks to provide insights into how AI can redefine personalized learning, enabling more precise definitions. The findings emphasize the use of PL terms in technological contexts and call for a unified term to enhance clarity and effectiveness in educational technology practices. Ultimately, the review aims to inform educators and policymakers about precise terms defining personalized learning in the AI context.

Keywords: Personalized learning, Adaptive learning, Learning, Customized learning, Individualized instruction, Intelligent tutoring systems, Personalized adaptive learning, Systematic review

Introduction

Personalized learning (PL) is a learner-centered approach that tailors instruction to learners' needs, goals, abilities, motivations, and interests (Schmid et al., 2022), enabling differentiated learning pathways that support academic development (Xie et al., 2019). With advances in digital technologies, PL has increasingly been implemented through data-driven and adaptive systems. However, the expansion of PL has also produced conceptual ambiguity, as related terms such as adaptive learning, individualized instruction, and customized learning are often used interchangeably. Shemshack and Spector's (2020) systematic review highlighted this lack of definitional clarity and mapped the overlapping terminology used across the literature.

© The Author(s) 2026. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

Springer

Since that review, artificial intelligence (AI) has become deeply embedded in educational technologies, enabling real-time feedback, adaptive sequencing, intelligent tutoring, and dynamic learning pathways that further reshape how personalization is designed and enacted (Castro et al., 2024; Katiyar et al., 2024). These developments suggest that both the meaning and operationalization of personalized learning have evolved. Accordingly, the present review extends Shemshack and Spector's (2020) work by examining recent definitions of PL and related terms in AI-driven educational contexts, with the aim of clarifying how personalized learning is being redefined in the AI era.

Research gaps and rationale for redefinition

Recent advances in artificial intelligence have transformed personalized learning from static, one-size-fits-all instruction into adaptive, data-driven, and learner-centered approaches that support real-time feedback, individualized content, and dynamic learning pathways, thereby enhancing engagement, motivation, and academic outcomes (Castro et al., 2024; Katiyar et al., 2024). Emerging technologies such as generative AI, intelligent tutoring systems, and learning analytics are increasingly regarded as transformative, with the potential to expand access and promote educational equity (Kanta, 2023; Taşkın, 2025).

Despite these developments, substantial gaps persist in theory and research. Current frameworks often lag behind technological innovation, and critical concerns—including data privacy, algorithmic bias, ethical issues, teacher preparation, and human–AI collaboration—remain insufficiently addressed (Castro et al., 2024; Laak & Aru, 2024). Furthermore, there is a lack of longitudinal, inclusive, and methodologically rigorous research, particularly in underrepresented populations and diverse educational contexts (Bayly-Castaneda et al., 2024; Halkiopoulos & Gkintoni, 2024; Laak & Aru, 2024). Although some reviews examine specific AI applications, few systematically analyze how AI is reshaping the conceptual foundations of personalized learning or map future research directions (Bayly-Castaneda et al., 2024; Castro et al., 2024).

This gap is most evident in the absence of updated syntheses that reconsider definitions and terminology in light of recent AI developments. While studies increasingly show that AI has redefined personalized learning through adaptive, data-driven, and individualized environments (Castro et al., 2024; Deckker et al., 2025; Katiyar et al., 2024), conceptual clarity, inclusivity, and empirical validation remain limited (Bhutoria, 2022; Laak & Aru, 2024). Consequently, there is a pressing need to clarify how overlapping concepts are defined, operationalized, and theoretically integrated within AI-supported educational contexts.

Guided by this gap, the present systematic review addresses the central research question:

What are the similarities and differences among the terms used to describe personalized learning approaches in the era of artificial intelligence?

To systematically examine this question and establish a coherent theoretical foundation, the study further investigates the following sub-questions:

1. How is personalized learning defined in recent literature, and what are its core components?
2. How has adaptive learning been used, and how does it relate to AI-driven personalized learning?
3. How has individualized instruction been conceptualized, and how does it connect to AI-assisted personalized learning?
4. How is customized learning related to personalized learning in AI-supported environments?
5. How is personalized adaptive learning connected to broader conceptions of personalized learning?
6. How is intelligent tutoring positioned in relation to personalized learning frameworks?
7. What roles do teachers and AI systems play in the design and implementation of personalized learning?

By addressing these questions, this review seeks not only to map conceptual similarities and differences among commonly used terms, but also *to develop a unifying definition of personalized learning* that integrates its essential components within contemporary AI-driven educational contexts.

Personalized learning

Personalized learning (PL) is a learner-centered approach that tailors instruction to learners' needs, goals, abilities, motivations, and interests (Schmid et al., 2022), enabling differentiated learning pathways that support academic development (Xie et al., 2019). Although advances in digital technologies have increasingly supported PL through data-driven and adaptive systems, the field remains conceptually ambiguous, with related terms such as adaptive learning, individualized instruction, and customized learning often used interchangeably; Shemshack and Spector's (2020) systematic review highlighted this lack of definitional clarity and mapped overlapping terminology in the literature. Since that review, artificial intelligence (AI) has become deeply embedded in educational technologies, enabling real-time feedback, adaptive sequencing, intelligent tutoring, and dynamic learning pathways (Castro et al., 2024; Katiyar et al., 2024), suggesting that the meaning and operationalization of personalized learning have evolved. Accordingly, the present review extends Shemshack and Spector's (2020) work by examining recent definitions of PL and related terms in AI-driven educational contexts to clarify how personalized learning is being redefined in the AI era.

Adaptive learning

Adaptive learning and personalized learning are often used interchangeably, yet they represent distinct, overlapping concepts within technology-enhanced education (Shemshack & Spector, 2020; Wang et al., 2024; Xie et al., 2019). Adaptive learning is typically system-centered, using AI, machine learning, and computational models to algorithmically adjust difficulty, pacing, and content based on learner performance (Mirata et al., 2020; Shemshack & Spector, 2020; Wang et al., 2020; Xie et al., 2019), whereas personalized learning constitutes a broader, learner-centered paradigm that incorporates

learners' goals, interests, abilities, and self-regulatory processes (Ipinnaiye & Risquez, 2024; Xie et al., 2019). Although the boundary between the two is often blurred (Xie et al., 2019), the literature generally characterizes adaptive learning as a technology-driven subset of personalized learning, as AI-enhanced systems primarily optimize instructional sequences without fully integrating broader learner attributes, even in large-scale contexts such as MOOCs (Hooshyar et al., 2024; Kaiss et al., 2023; Mejeh & Rehm, 2024; Shemshack & Spector, 2020; Wang et al., 2024; Yu & Chauhan, 2024; Zhao, 2025).

Individualized instruction

Individualized instruction tailors pacing, methods, and content to learners' abilities, interests, and goals to enhance relevance, motivation, and engagement (Ackermans et al., 2024; Zhao, 2025; Zou et al., 2020), requiring both teacher digital pedagogy and learner digital literacy in technology-enhanced environments (Li & Wong, 2020; Xu et al., 2024). Advances in artificial intelligence have expanded individualized instruction through AI-assisted personalization, enabling real-time data analysis, adaptive content, targeted feedback, immersive and accessible learning tools, and individualized plans for diverse learners (Xie et al., 2019; Yu & Chauhan, 2024; Zhao, 2025). While individualized instruction primarily adapts the pace of progress through predetermined curricula (Schmid et al., 2022), personalized learning entails broader customization of objectives, content, methods, and sequencing, emphasizing learner "choice and voice" (Schmid & Petko, 2019; Schmid et al., 2022; Xie et al., 2019; Zou et al., 2020), with AI systems further operationalizing individualized pathways based on learner profiles and competencies (Bendahmane et al., 2019).

Customized learning

In AI-enhanced educational contexts, customized learning is conceptualized as a core component and practical operationalization of personalized learning, which tailors instruction to learners' needs, preferences, and progress within an overarching learner-centered framework (Xie et al., 2019; Yu & Chauhan, 2024; Zhao, 2025; El-Sabagh, n.d.). Customization provides the technological and pedagogical mechanisms—such as AI-driven content delivery, individualized pacing, adaptive feedback, and real-time adjustment—through which personalization is enacted, transforming digital environments into dynamic systems responsive to learner diversity (Xie et al., 2019; Yu & Chauhan, 2024; Zhao, 2025 Kaouni et al., 2023). Empirical studies indicate that AI-based customization enhances engagement, critical thinking, learning effectiveness, and learner autonomy by aligning learning paths, resources, and interfaces with individual profiles (Almuhanna, 2024; Hooshyar et al., 2024; Kolekar et al., 2018; Nguyen et al., 2023).

Intelligent tutoring

Intelligent Tutoring Systems (ITS) are a major technological application within personalized learning, using artificial intelligence, machine learning, and computational algorithms to deliver adaptive, individualized instruction and real-time feedback based on learner data, behaviors, and preferences (Hibbi et al., 2021; Mousavinasab et al., 2018; Yu & Chauhan, 2024). Recent advances in NLP, deep learning, and big-data analytics

have strengthened ITS personalization through sophisticated learner modeling, tailored recommendations, and large-scale instructional support, including recommender-based and hybrid human-AI systems that enhance engagement, performance, and teacher support (Beyyoudh et al., 2019; Hobert & Berens, 2023; Huiji, 2022; Troussas et al., 2020; Zayet et al., 2022; Zhao, 2025). While ITS effectively operationalize personalization, they remain a specific technological instantiation within the broader pedagogical framework of personalized learning, which extends beyond ITS alone (Hibbi et al., 2021; Xie et al., 2019; Yu & Chauhan, 2024).

Personalized adaptive learning

Personalized and adaptive learning is a widely recognized and extensively studied concept in contemporary education. Personalized learning is increasingly conceptualized as an AI-driven, dynamically adaptive process that customizes content and feedback based on individual learner performance and motivational states (Liu, 2024). The sustained volume of academic publications and growing institutional interest confirm its prominence in research and practice (Mirata et al., 2020; Xie et al., 2019). However, despite the conceptual overlap, the compound term *"personalized adaptive learning"* remains rarely used in educational research, with studies more commonly referring to the constructs separately as either *"adaptive learning"* or *"personalized learning."*

Context-sensitive personalized learning in the AI era

Personalized learning is a core benefit of Artificial Intelligence in Education (AIED), defined as a learner-centered approach that adapts content, pacing, and instructional methods to individual needs (Mustafa et al., 2024). However, its effectiveness is highly context-dependent, varying according to learners' disciplinary backgrounds and stages of study. Evidence indicates that different student groups exhibit distinct learning trajectories and respond differently to personalized interventions, underscoring the need for context-aware rather than uniform personalization strategies (Gao et al., 2025).

Comparative analyses of Computer Science (CS) and Mathematics students in introductory programming courses reveal contrasting patterns of engagement and performance. CS students tend to develop more efficient learning strategies over time, showing reduced surface engagement alongside increased productivity and conceptual mastery (Gao et al., 2025). In contrast, Mathematics students often display high engagement without corresponding achievement, characterized by complex but inefficient work and greater susceptibility to learning avoidance—performing adequately on formative tasks yet underperforming in summative assessments (Gao et al., 2025). These differences are linked to goal congruity: CS students typically perceive programming as central to their academic and professional trajectories, whereas Mathematics students may regard it as less relevant, resulting in more superficial engagement (Gao et al., 2025).

These findings suggest that effective AI-driven personalized learning must account for learners' academic backgrounds, motivations, and disciplinary contexts. For example, personalization for CS students may emphasize increased challenge and skill refinement, whereas for Mathematics students it should address low initial engagement and learning avoidance through structured scaffolding and domain-relevant applications (Gao et al., 2025). Overall, personalized learning in the AI era requires

a nuanced, context-sensitive approach that aligns instructional strategies with the specific needs, goals, and learning profiles of diverse learner populations (Gao et al., 2025; Mustafa et al., 2024).

Core ethical challenges

AI-driven personalized learning systems require large amounts of student data, making data privacy and security a primary concern. Risks include unauthorized data access, misuse, and lack of student control over personal information. Robust data protection, anonymization, and clear consent protocols are essential to safeguard privacy (García-López & Trujillo-Liñán, 2025; Xu, 2025; Yu & Guo, 2023). Algorithmic fairness and bias are equally critical. AI models can unintentionally perpetuate or amplify existing inequalities if trained on biased data, leading to unfair educational outcomes for marginalized groups. Regular bias audits, diverse datasets, and fairness-aware algorithms are recommended to mitigate these risks (Chinta et al., 2024; García-López & Trujillo-Liñán, 2025; Yu & Guo, 2023).

Furthermore, transparency and explainability are necessary for trust and accountability in personalized learning processes. Many AI systems operate as "black boxes," making it difficult for educators and students to understand or challenge decisions. Explainable AI models and transparent data practices are needed to ensure accountability and foster trust (García-López & Trujillo-Liñán, 2025; Chinta et al., 2024; Lepri et al., 2021). However, ethical considerations—especially data privacy, algorithmic fairness, and transparency—are central to the responsible use of AI in personalized learning. Addressing these challenges requires technical safeguards, robust governance, and a human-centered approach to ensure educational innovation benefits all learners equitably.

Research methodology

For this review, the guidelines published by Okoli (2015) for conducting systematic literature reviews in Information Systems Research were applied. Okoli's framework offers a comprehensive approach to conducting such reviews, with a strong foundation in information technology. Given that this review is similarly grounded in the field of information technology, Okoli's methodology was considered a suitable model for guiding the process. The researchers discussed the previously studied terms: personalized learning, adaptive learning, customized learning, and individualized instruction.

As suggested by the authors Shemshack and Spector (2020), personalized adaptive learning was added to the terms in addition to the term intelligent tutoring, as it's frequently used in today's research on personalized learning. These terms overlap significantly, all emphasizing the use of technology to support personalization in education for individual learners. The variety and interchangeable use of these terms highlight the lack of a single, unified definition for personalized learning, which can be an obstacle to research progress in the field. Therefore, this review aims to clarify these definitions and their interrelationships, providing a more coherent framework to guide future research and practice in personalized learning. Figure 1 displays the process of PRISMA for data collection and analysis.

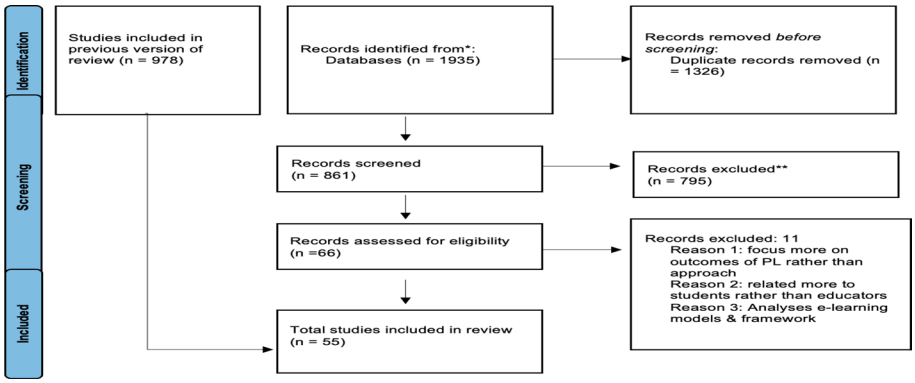


Fig. 1 The process of PRISMA for data collection and analysis

Review design

This study utilized a systematic review methodology to identify, evaluate, and synthesize peer-reviewed literature on the evolving terminology and conceptualization of AI-driven personalized learning. The review adhered to the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Page et al., 2021), which are designed to ensure methodological transparency, rigor, and reproducibility.

Sources of literature

To address the research question, the researchers selected several well-established and reputable databases to serve as the foundation for this systematic review. These include Scopus, ScienceDirect, EBSCOhost, IEEE Xplore, JSTOR, and Web of Science, ensuring comprehensive coverage of journals relevant to the field. The most pertinent journals for the systematic review were consistently selected from these databases. Additionally, the h5-index for the "Educational Technology" category on Google Scholar was used as an initial reference point, as this category directly relates to studies on personalized learning. Table 1 presents the databases utilized in this review.

Supplementary procedures

Relevant papers were first located through conventional searches of online databases and academic journals. These papers were then examined to assess their relevance and suitability for inclusion in the study. To keep the scope of the review both focused and manageable, the top nine journals from the "Educational Technology" category on Google Scholar's h5-index were chosen. This approach aimed to balance breadth and depth, ensuring enough high-quality studies were included to answer the research question effectively. Subsequently, most journals in the field of educational technology were indexed, and the SCImago Journal Rank (SJR) was used to assess their impact. Although the impact factor rankings did not always align perfectly with Google Scholar's h5-index, the selected journals represent the most influential publications in educational technology. For instance, although the 'Computer

Table 1 The Search Results for "Personalized Learning" for Selected Databases

Database name	#Results for initial search on "personalized learning"	Main journals listed (#journal articles)
EBSCOhost	1506	Educational Technology Research And Development (78) British Journal Of Educational Technology (67) Education And Information Technologies (57) Interactive Learning Environments (35) Smart Learning Environments (12) Computers & Education (11) Journal Of Research On Technology In Education (10) Journal Of Computer Assisted Learning (7) International Review Of Research In Open And Distributed Learning (7) Australasian Journal Of Educational Technology (1) Computer Assisted Language Learning (1) Journal Of Educational Computing Research (1) Learning, Media And Technology (1)
Scopus	5617	Education And Information Technologies (71) International Journal Of Emerging Technologies In Learning (37) Interactive Learning Environments (36) Computers And Education Artificial Intelligence (19) Computer & Education (13) International Journal Of Educational Technology In Higher Education (11) British Journal Of Educational Technology (18) Techtrends (18) Smart Learning Environments (14)
Sciencedirect	3013	Computers And Education: Artificial Intelligence (191) Computers & Education (120)
Web of Science	2966	Education And Information Technologies (63) Interactive Learning Environments (32) Techtrends (16) International Journal Of Emerging Technologies In Learning (14) Journal Of Research On Technology In Education (13) Smart Learning Environments (12) International Journal Of Educational Technology In Higher Education (11) International Review Of Research In Open And Distributed Learning (7) Journal Of Computers In Education (7) British Journal Of Educational Technology (4) Learning Media And Technology (4) Techtrends For Leaders In Education D5training (D51)
IEEE Xplore	1,302	IEEE Access(63) IEEE Transactions On Learning Technologies(19) IEEE Internet Of Things Journal(7) IEEE Transactions On Education(5)
JSTOR	524	Educational Technology Research And Development (39)

Assisted Language Learning' journal appeared as highly ranked in Google Scholar, it was excluded from the review due to the absence of qualifying articles based on the review's selection criteria.

Only peer-reviewed articles from online academic journals were included, as these sources are recognized for their credibility and reliability. Such journals provide verifiable, data-rich content, enhancing the reliability and depth of the literature review. A clearly defined method was followed for journal selection to maintain methodological rigor and scientific consistency. The researchers review the main databases for educational technology to ensure all relevant journals of the field are included. This review is solely focused on journals to keep the scope of the review manageable and present

Table 2 The Google Scholar H5-index and Journal Impact for Selected Journals

Journal Name	The google scholar h5-index & list order	Journal impact factor according to SJR
Computers & Education	1–154	3.343 Q1
Education and Information Technologies	2–112	1.654 Q1
British Journal of Educational Technology	3–101	2.690 Q1
Interactive Learning Environments	4–85	1.976 Q1
*Computer Assisted Language Learning	5–79	3.513 Q1
International Journal of Instruction	6–79	not available
International Journal of Educational Technology in Higher Education	7–77	3.912 Q1
International Journal of Emerging Technologies in Learning (iJET)	8–76	not available
Educational Technology Research and Development	9–72	1.429 Q1

* Even though Computer Assisted Language Learning was listed on Google Scholar and showed having a high impact on education technology, researchers have not located any qualified papers according to selection procedures; thus this journal was eliminated from review

reviewed data to create a resource for future studies. Table 2 lists the journals included in this review.

Search query

A suitable search query was developed to identify relevant studies on personalized learning. The search query was as follows: (Publication Title: ("journal name")) AND ("term") and the journals listed in the table were searched for each of following terms: "personalized learning", "adaptive learning", "individualized instruction", "customized learning", "intelligent tutoring", and "personalized adaptive learning".

Inclusion/exclusion criteria

To determine the final set of papers for review, a four-phase selection process was established based on specific inclusion criteria.

In Phase One, an initial search was conducted using key terms such as "personalized learning", "adaptive learning", "individualized instruction", "customized learning", "intelligent tutoring", and "personalized adaptive learning". The search was limited to publications from 2019 to 2025 to focus on recent developments in personalized learning, a topic of increasing interest among researchers and policymakers. Only English-language articles were considered to avoid delays related to translation. Further filters included papers that addressed technology integration and were categorized as research articles published in peer-reviewed scientific journals. This helped maintain a manageable review scope.

Phase Two involved screening by title, abstract, and keywords. Researchers examined each result from the initial search and selected studies that appeared relevant to the topic.

Phase three represented the full-text screening phase, during which the entire content of each article was reviewed to determine whether it offered definitions or discussed the terminology associated with personalized learning. Only papers accessible via open-access sources or the researchers' institutional library were included.

Phase Four entailed downloading and then uploading the eligible papers into the Rayyan application, where they were organized into subfolders based on their respective journal databases. Each full article was read thoroughly to identify definitions and key components of personalized learning. Papers that met all inclusion criteria were starred and reread to confirm their relevance to the review.

An initial search on Google Scholar using the term *"personalized learning"* revealed a steady increase in the number of publications over the years, with a notable spike around 2024 (see Fig. 1). The review focused on articles from 2019 onwards, aligning with the rising interest in personalized learning as technology became more prominent in education and artificial intelligence evolved.

Results

This section presents the findings of the systematic review on how key terms related to personalized learning have been conceptualized and used in educational technology literature between 2019 and 2025. Following a multi-stage screening process, 55 studies were included in the final corpus (see Fig. 2 and Table 1 for journal distribution and term usage). Nine journals were searched using the terms *personalized learning*, *adaptive learning*, *individualized instruction*, *customized learning*, *intelligent tutoring*, and *personalized adaptive learning*. After screening 861 papers across four phases, 55 high-quality studies met the inclusion criteria and are marked with an asterisk in the reference list.

As shown in Fig. 3, terminology was used unevenly across the corpus. Personalized learning accounted for just over half of the studies (28; 50.9%), followed by adaptive learning (13; 23.6%) and intelligent tutoring (9; 16.4%). In contrast, individualized instruction (1; 1.8%), customized learning (2; 3.6%), and personalized adaptive learning (2; 3.6%) appeared infrequently. The findings are organized according to the seven research questions guiding this review.

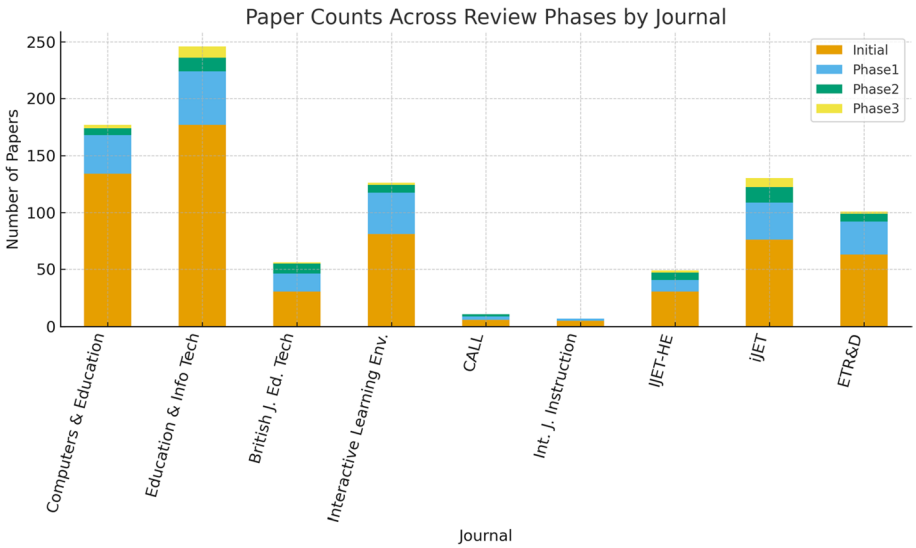


Fig. 2 Result for the Number of Papers of "Personalized Learning" in Each Research Phase by Journal

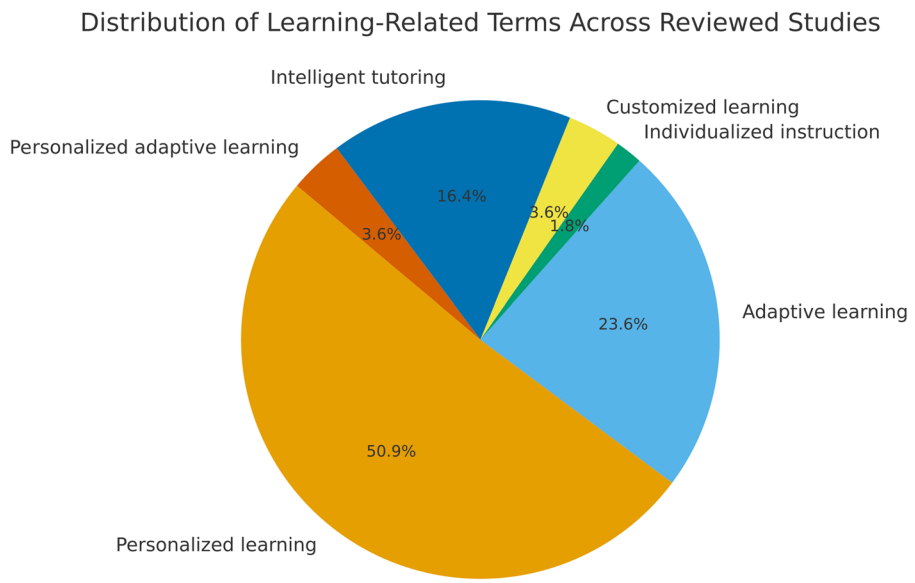


Fig. 3 Result-set size for the number of papers of "personalized learning", "adaptive learning", "individualized instruction", "customized learning", "intelligent tutoring", & "personalized adaptive learning" by the journal

Research Question 1: How is Personalized Learning Defined and What Are Its Core Components?

Across the 28 studies using personalized learning as the primary term, definitions converged on tailoring content, pacing, and support to individual learner needs, characteristics, and goals, consistently framing PL as learner-centered, goal-oriented, and flexible rather than uniform (Bernacki et al., 2021; Shemshack & Spector, 2020). Many studies emphasized the role of digital environments in collecting and analyzing learner data to guide content sequencing, difficulty, feedback, and modality, positioning personalization as a data-driven process enabled by analytics and algorithmic decision-making (Murad et al., 2020; Wang et al., 2022; Zheng et al., 2024). Several works further introduced Digital Personalized Learning (DPL), distinguishing between integrated and standalone tools in technology-rich contexts, with integrated approaches more closely aligned with institutional strategies (Van Schoors et al., 2021; Vanbecelaere et al., 2023). Overall, personalized learning was portrayed as a flexible, technology-mediated, and data-informed approach that optimizes individual learning while remaining aligned with curricular and institutional constraints.

Research Question 2: How Is Adaptive Learning Used and How Does It Relate to AI-Driven Personalized Learning?

Adaptive learning appeared in 13 studies and was consistently described as the primary mechanism through which personalization is operationalized, dynamically adjusting task difficulty, learning sequences, feedback, and pacing based on learner data (Barbosa et al., 2023; El-Sabagh, 2021; Ipinnaiye & Risquez, 2024). Many studies adopted the three-component model (learner, content, and instructional models), in which algorithms translate performance, interaction, self-report, and motivational data into instructional adaptations (Li, 2023a, 2023b; Liu, 2024; Martin et al., 2020a, 2020b; Wang et al., 2024; Xie et al., 2019). Most applications were in higher

education—particularly computer science, language learning, and mathematics—with positive effects on achievement, engagement, and efficiency reported across quasi-experimental and design-based studies (Hooshyar et al., 2024; Wang et al., 2020). Overall, the literature positions adaptive learning as the algorithmic "engine" of personalized learning, providing the technical means for continuous, data-driven tailoring.

Research Question 3: How Is Individualized Instruction Related to AI-Assisted Personalized Learning?

Only one study used *individualized instruction* as its primary term, indicating that it has largely receded in recent AI-focused literature; where it appeared, it referred to teacher-designed variation in content and pacing based on professional judgment rather than automated analytics. In contrast, AI-assisted personalized learning relies on learner models, algorithmic recommendations, and data-driven adaptation (Ackermans et al., 2024; Wang et al., 2024; Zhang et al., 2022), suggesting that individualized instruction functions as a pedagogical predecessor to AI-based personalization. While both emphasize responsiveness to learner needs, they differ in scale, automation, and data use, with emerging hybrid models combining teacher expertise and system-generated recommendations (Lee et al., 2021; Schmid et al., 2022).

Research Question 4: How Is Customized Learning Connected to Personalized Learning in AI Contexts?

Two studies used *customized learning* as a primary term. Customized learning generally referred to tailoring materials, tasks, or pathways based on learner preferences or choices, often supported by digital tools for content selection (Almuhanna, 2024; Wang et al., 2022).

In AI-supported environments, customization was typically implemented through recommender systems that matched resources to learner profiles using performance data, inferred interests, or learning styles (Murad et al., 2020; Wan & Yu, 2020; Zayet et al., 2022). Unlike fully adaptive systems, customization was often episodic or user-initiated rather than continuously adaptive. Conceptually, customized learning represents a dimension of personalized learning—particularly content personalization—rather than a distinct paradigm.

Research Question 5: How Is Personalized Adaptive Learning Related to Personalized Learning?

Two studies explicitly addressed *personalized adaptive learning*, describing systems that integrate learner profiles with real-time adaptation based on performance and engagement data (Luo et al., 2025; Zheng et al., 2024). These systems employed advanced learning-path algorithms, knowledge tracing, and predictive models to recommend instructional sequences. Findings indicated improvements in learning efficiency and performance compared to static or teacher-paced approaches. Personalized adaptive learning thus represents a highly integrated operationalization of personalized learning in AI-enhanced environments, aligning with calls for systems that combine learner modeling, adaptivity, and human oversight (Hashim et al., 2022; Mustafa et al., 2024).

Research Question 6: How Is Intelligent Tutoring Connected to Personalized Learning?

Nine studies examined Intelligent Tutoring Systems (ITS), defining them as computer-based environments that emulate human tutoring through step-by-step guidance, adaptive feedback, and individualized practice (Mousavinasab et al., 2018; Xu et al., 2019). These systems employed AI techniques such as rule-based reasoning, Bayesian networks, recommender algorithms, and natural language processing (Beyyoudh et al., 2019; Hibbi et al., 2021; Hobert & Berens, 2023). Most studies reported positive learning outcomes, particularly in programming, mathematics, and STEM, with recent work also addressing motivational and affective dimensions through emotion recognition, gamification, and conversational agents (Li, 2023a, 2023b; Liu, 2024; Yu & Chauhan, 2024). Overall, ITS represent one of the most mature and technologically sophisticated implementations of AI-driven personalized learning.

Research Question 7: What Roles Do Teachers and AI Systems Play in Personalized Learning?

Findings across studies indicate that personalized learning functions as a collaborative human–AI model in which teachers and AI systems play complementary roles. Teachers lead design, implementation, and evaluation by interpreting learner data, aligning system recommendations with curricular goals, providing socio-emotional support, and intervening when automated pathways conflict with learner needs (Hobert & Berens, 2023; Lee et al., 2021). AI systems contribute through learner modeling, real-time adaptation, and continuous analytics, generating learner profiles, predicting performance, personalizing content, and monitoring engagement (Barbosa et al., 2023; Luo et al., 2025). Together, these findings suggest that personalized learning is most effective when AI provides adaptive precision while teachers ensure pedagogical coherence, ethical oversight, and human involvement.

Moreover, AI systems in personalized learning contribute primarily through data-driven modeling, real-time adaptation, and continuous analytics. In the design phase, they generate learner profiles, predict performance, and propose content sequences using machine learning, recommender systems, and cognitive modeling (Bendahmane et al., 2019; Murad et al., 2020; Wang et al., 2024; Zine et al., 2019). During implementation, AI personalizes learning by adjusting difficulty, pacing, modality, and feedback, with intelligent tutoring systems providing immediate corrective feedback and identifying misconceptions (Barbosa et al., 2023; Beyyoudh et al., 2019; El-Sabagh, 2021; Hibbi et al., 2021). In evaluation, AI analytics monitor progress, engagement, and risk patterns to identify learners requiring support (Huiji, 2022; Ipinnaiye & Risquez, 2024; Li, 2023a, 2023b; Luo et al., 2025). Overall, AI enhances scalability and precision, while teachers ensure pedagogical integrity, ethical oversight, and human connection, making personalized learning most effective when both function as interdependent partners.

Synthesizing findings across terms and implementations (e.g., Bernacki et al., 2021; Hashim et al., 2022; Martin et al., 2020a, 2020b; Shemshack & Spector, 2020), eight core components emerged as essential to a comprehensive definition of AI-supported personalized learning: (1) learner profile, (2) data inputs, (3) content model, (4) instructional model, (5) adaptive engine, (6) interface and user controls, (7) personalization goals, and (8) evaluation and governance. These components highlight that personalized learning in AI-rich contexts is best understood as a socio-technical system integrating pedagogical design, algorithmic processes, and ethical governance. Although multiple terms are

used in policy and practice, research usage is increasingly concentrated around *personalized learning*, *adaptive learning*, and *intelligent tutoring*.

The concept of *Digital Personalized Learning (DPL)* (Vanbecelaere et al., 2023) offers a promising unifying framework, encompassing the cognitive, emotional, motivational, and efficiency dimensions of learning in technology-mediated environments. DPL emphasizes both integrated and standalone implementations, with integrated use being more prevalent.

Existing and emerging trends

Research in e-learning increasingly emphasizes personalization and adaptivity to address individual differences in learners' needs, abilities, and learning patterns. A major trend is the development of personalized recommender systems (PRS), particularly in K–12 education, which aim to enhance engagement and performance by integrating student profiling, content processing, and recommendation mechanisms (Martin et al., 2020a, 2020b; Zayet et al., 2022). Student profiling is becoming more sophisticated, incorporating not only performance data but also learning characteristics and psychological factors to create holistic learner models.

Another prominent trend is adaptive learning, which dynamically adjusts content, feedback, and navigation based on learner interactions. Research has expanded from focusing solely on learner models to integrating content and instructional models, forming comprehensive adaptive systems (Martin et al., 2020a, 2020b). Although most studies have been conducted in higher education—especially in computer science—there is a recognized need for research in more diverse contexts, including K–12 and informal learning (Zayet et al., 2022).

Intelligent Tutoring Systems (ITS) represent a mature strand of personalized learning, using AI techniques such as rule-based reasoning, data mining, and Bayesian networks to deliver individualized feedback and instruction (Mousavinasab et al., 2018). Emerging developments include emotionally intelligent systems, conversational agents, emotion recognition technologies, serious games for assessment, and a shift toward mobile-based platforms to enhance accessibility and learner engagement (Beyyoudh et al., 2019; Xie et al., 2019; Yu & Chauhan, 2024).

Overall, the field is moving from static, one-size-fits-all e-learning toward complex, data-driven, and holistic personalized systems that integrate cognitive, behavioral, and affective dimensions of learning. Future research is expected to validate these approaches across diverse educational levels, refine learner modeling techniques, and evaluate the effectiveness of adaptive strategies in supporting individualized learning and growth.

Discussion

Personalized learning is an educational approach that adapts instruction to learners' needs, preferences, and pacing. Although rooted in traditional practices such as tutoring and apprenticeships, it has been fundamentally reshaped by digital technologies and, more recently, artificial intelligence (AI). In contemporary technology-enhanced learning, personalized learning encompasses related concepts such as adaptive learning, individualized instruction, customized learning, and intelligent tutoring, which are often

grouped under "personalized TEL" despite important differences in focus and implementation (Hooshyar et al., 2024). A core principle of personalized learning is achieving alignment among ICT, learners, educators, and instructional content to sustain motivation and learning effectiveness (Romi, 2023). AI-driven personalization enhances engagement, inclusivity, and learner well-being, particularly for students with special needs, and supports innovations such as conversational tutors and smart learning environments (Li, 2023a, 2023b; Walter, 2024; Yu & Chauhan, 2024).

Despite its potential, research indicates that educational institutions underutilize digital technologies for personalized learning, revealing a persistent gap between technological capability and classroom practice (Schmid et al., 2022). Addressing this gap requires stronger professional development, improved integration of technology, and pedagogical frameworks that incorporate interactivity, gamification, and individualized assessment (Alé-Ruiz et al., 2023; Leshchenko et al., 2023). Personalized learning further aims to ensure coherence across learning pathways by aligning knowledge units and prerequisites to reduce cognitive overload and enhance learner progression (Zheng et al., 2024).

Adaptive technologies constitute a major operational dimension of personalized learning, offering data-driven recommendations and continuous adjustment of instruction to learners' real-time needs (Smyrnova-Trybulska et al., 2022; Wang et al., 2020). Learning management systems such as Moodle exemplify this approach by tailoring content, pacing, and assessment based on learner performance, while still requiring meaningful human mentoring to guide instructional design (Barbosa et al., 2023; Smyrnova-Trybulska et al., 2022). Although adaptive learning, intelligent tutoring, and personalized learning are frequently used interchangeably in academic discourse, adaptive learning remains the most prevalent term following personalized learning, whereas intelligent tutoring and customized learning are more commonly associated with specific digital systems (Elmaadaway & Abouelenein, 2022).

Recent reviews indicate that while the fundamental goal of personalized learning—tailoring education to individual learners—remains stable, its terminology and conceptual foundations have become increasingly data-driven and precise in the AI era. Earlier literature noted significant conceptual overlap and ambiguity among personalization-related terms (Bernacki et al., 2021; Hashim et al., 2022; Shemshack & Spector, 2020), whereas contemporary work emphasizes AI-enabled learner profiling, adaptive content delivery, and automated feedback as defining features of modern personalized learning frameworks (Castro et al., 2024).

Conclusion & implications

The field of personalized learning is rapidly evolving in response to technological advances and deeper insights into human–machine interaction. While this evolution presents significant opportunities, it also underscores the need for clearer conceptual frameworks and coordinated adaptation to emerging technologies. At present, students, educators, researchers, and policymakers face persistent challenges related to conceptual ambiguity, implementation barriers, and methodological limitations. A central issue is the absence of a universally accepted definition of personalized learning, which continues to function as a broad, multi-layered umbrella term encompassing diverse student-centered approaches (Ackermans et al., 2024; Schmid & Petko, 2019). Moreover,

existing research disproportionately focuses on older learners, leaving substantial gaps in understanding the long-term effects of personalized learning on younger, elementary-aged students (Schmid & Petko, 2019).

From a policy and practice perspective, effective school-wide implementation is often constrained by insufficient technological infrastructure and inconsistent integration strategies. Schools frequently adopt personalized learning without coherent institutional frameworks, resulting in fragmented and teacher-dependent use of digital tools (Schmid et al., 2022; Xie et al., 2019). Methodologically, much of the literature relies on cross-sectional designs and self-report data, limiting causal inference and increasing the risk of bias (Schmid et al., 2022). Although personalized learning increasingly leverages data mining and adaptive technologies to enhance engagement and outcomes (Yang & Alabool, 2022), the complexity of educational environments complicates efforts to isolate the effects of specific interventions (Ackermans et al., 2024). Additionally, disruptions during the COVID-19 pandemic—particularly declines in student motivation and self-regulation—further challenge the interpretation of recent findings and reinforce the need for more rigorous, longitudinal research, especially with younger learners (Ackermans et al., 2024).

Overall, advancing personalized learning requires the development of clearer conceptual definitions, the removal of infrastructural and organizational barriers, and the adoption of more robust empirical methodologies. Future research should extend to underrepresented learner populations and explicitly address cognitive and motivational processes such as metacognition, rather than assuming they will emerge from technological implementation alone (Ackermans et al., 2024). Although recent evidence confirms that adaptive and personalized learning has become central within educational technology, the field continues to face significant gaps in theory, inclusivity, and empirical validation. Consequently, new reviews must articulate their unique contributions, address unresolved research gaps, and advance more equitable and effective AI-enhanced educational practices.

Limitations

This study faced several limitations related to the scope and management of the literature review. The large volume of publications on the topic created the possibility that some relevant studies were unintentionally omitted, a common challenge in extensive reviews. Although multiple reference management tools were used to organize and streamline the process, the review was restricted to English-language, peer-reviewed articles from nine high-impact journals, potentially excluding valuable findings from other ranked journals, non-English sources, and alternative scholarly formats such as conference papers, dissertations, and reports.

Future research

The findings of this review emphasize the need for greater conceptual clarity in defining personalized learning in AI-driven educational contexts, encouraging the use of more precise terminology—such as digital personalized learning (DPL) or personalized adaptive learning—to better reflect the roles of AI and system-level adaptation. Advancing this agenda also requires closer collaboration between AI developers and educators to

ensure that emerging tools are pedagogically sound, user-friendly, and responsive to evolving educational needs (Yu & Chauhan, 2024).

The review further highlights the importance of integrating technology-based diagnostic assessment to address both cognitive and emotional dimensions of learning, with greater emphasis on higher-order thinking and the responsible integration of emerging technologies while considering ethical and privacy implications. Finally, it calls for systematic, comparative evaluations of personalized adaptive learning platforms to assess effectiveness across learner profiles, instructional contexts, and educational goals, supporting more informed adoption of personalized learning technologies.

Abbreviations

PL	Personalized learning
AI	Artificial intelligence
GenAI	Generative artificial intelligence
TEL	Technology enhanced learning
NLP	Natural language processing
DPL	Digital personalized learning
SJR	Scimago journal rank
OECD	Organization for economic co-operation and development
ITS	Intelligent tutoring system
PRS	Personalized recommender systems

Acknowledgements
Not applicable.

Author contributions
Each author contributed evenly to this paper. All authors read and approved the final manuscript.

Funding
Not applicable.

Data availability
Detailed data sets can be requested via the corresponding author.

Declarations

Conflict of interest
The manuscript entitled "Redefining Personalized Learning in the Artificial Intelligence Era: An Updated Systematic Review from 2019 to 2025" is our original work and has not been published previously, nor is it under consideration for publication elsewhere. All authors have significantly contributed to the research, writing, and revision of this manuscript, and all have approved the final version for submission. There is no conflict of interest to declare related to this work.

Received: 11 August 2025 Accepted: 1 February 2026
Published online: 27 February 2026

References

The papers identified for systematic literature review are marked in the references with an asterisk (*)

*Ackermans, K., Bakker, M., van Loon, A.-M., Kral, M., & Camp, G. (2024). Young learners' motivation, self-regulation, and performance in personalized learning. *Computers & Education*. https://doi.org/10.1016/j.compedu.2024.105208

*Alé-Ruiz, R., Martínez-Abad, F., & del Moral-Marcos, M. T. (2023). Academic engagement and management of personalized active learning in higher education digital ecosystems. *Education and Information Technologies, 29*, 12289–12304. https://doi.org/10.1007/s10639-023-12358-4

*Almuhanna, M. A. (2024). Teachers' perspectives of integrating AI-powered technologies in K–12 education for creating customized learning materials and resources. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-13257-y

*Barbosa, P. L. S., do Carmo, R. A. F., Gomes, J. P. P., & Viana, W. (2023). Adaptive learning in computer science education. *Education and Information Technologies, 29*, 9139–9188. https://doi.org/10.1007/s10639-023-12066-z

Bayly-Castaneda, K., Ramirez-Montoya, M., Schrader, P., & Awidi, I. (2024). Crafting personalized learning paths with AI for lifelong learning: A systematic literature review. *Frontiers in Education*. https://doi.org/10.3389/feduc.2024.1424386

*Bendahmane, M., El Falaki, B., & Benattou, M. (2019). Toward a personalized learning path through a services-oriented approach. *International Journal of Emerging Technologies in Learning (iJET)*. https://doi.org/10.3991/ijet.v14i15.10951

*Bernacki, M., Greene, M., & Lobczowski, N. (2021). A systematic review of research on personalized learning: Personalized by whom, to what, how, and for what purpose(s)? *Educational Psychology Review, 33*, 1675–1715. https://doi.org/10.1007/s10648-021-09615-8

*Beyyoudh, M., Khalidi Idrissi, M., & Bennani, S. (2019). Towards a new generation of intelligent tutoring systems. *International Journal of Emerging Technologies in Learning, 14*(14), 105–121. https://doi.org/10.3991/ijet.v14i14.10664

Bhutoria, A. (2022). Personalized education and artificial intelligence in the United States, China, and India: A systematic review using a human-in-the-loop model. *Computers and Education: Artificial Intelligence, 3*, 100068. https://doi.org/10.1016/j.caeai.2022.100068

Castro, G., Chiappe, A., Rodríguez, D., & Sepulveda, F. (2024). Harnessing AI for education 4.0: Drivers of personalized learning. *Electronic Journal of e-Learning*. https://doi.org/10.34190/ejel.22.5.3467

Chinta, S., Wang, Z., Yin, Z., Hoang, N., Gonzalez, M., Quy, T., & Zhang, W. (2024). FairAIED: Navigating fairness, bias, and ethics in educational AI applications. *Frontiers in Education*. Advance online publication. https://doi.org/10.48550/arxiv.2407.18745

Deckker, D., Sumanasekara, S., & Fakhrou, A. (2025). AI-powered personalised learning: Promise and pitfalls. *World Journal of Advanced Research and Reviews*. https://doi.org/10.30574/wjarr.2025.26.3.2425

*Elmaadaway, M. A. N., & Abouelenein, Y. A. M. (2022). In-service teachers' TPACK development through an adaptive e-learning environment (ALE). *Education and Information Technologies*. https://doi.org/10.1007/s10639-022-11477-8

*El-Sabagh, H. A. (2021). Adaptive e-learning environment based on learning styles and its impact on development students' engagement. *International Journal of Educational Technology in Higher Education*. https://doi.org/10.1186/s41239-021-00289-4

Gao, Z., Yan, H., Liu, J., Zhang, X., Lin, Y., Zhang, Y., & Feng, J. (2025). Tracing distinct learning trajectories in an introductory programming course: A sequence analysis of score, engagement, and code metrics for novice computer science vs. math cohorts. *International Journal of STEM Education, 12*(1), 27.

García-López, I., & Trujillo-Liñán, L. (2025). Ethical and regulatory challenges of generative AI in education: A systematic review. *Frontiers in Education*. https://doi.org/10.3389/feduc.2025.1565938

Halkiopoulos, C., & Gkintoni, E. (2024). Leveraging AI in e-learning: Personalized learning and adaptive assessment through cognitive neuropsychology—A systematic analysis. *Electronics*. https://doi.org/10.3390/electronics13183762

Hashim, S., Omar, M., Jalil, H., & Sharef, N. (2022). Trends on technologies and artificial intelligence in education for personalized learning: Systematic literature review. *International Journal of Academic Research in Progressive Education and Development*. https://doi.org/10.6007/ijarped/v11-i1/12230

*Hibbi, F.-Z., Abdoun, O., & Haimoudi, E. K. (2021). Smart tutoring system: A predictive personalized feedback in a pedagogical sequence. *International Journal of Emerging Technologies in Learning (iJET)*. https://doi.org/10.3991/ijet.v16i20.24783

*Hobert, S., & Berens, F. (2023). Developing a digital tutor as an intermediary between students, teaching assistants, and lecturers. *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-023-10293-2

*Hooshyar, D., Weng, X., Sillat, P. J., Tammets, K., Wang, M., & Hämäläinen, R. (2024). The effectiveness of personalized technology-enhanced learning in higher education: A meta-analysis with association rule mining. *Computers & Education*. https://doi.org/10.1016/j.compedu.2024.105169

*Huiji, S. (2022). Big data-assisted recommendation of personalized learning resources and teaching decision support. *International Journal of Emerging Technologies in Learning*. https://doi.org/10.3991/ijet.v17i04.29585

*Ipinnaiye, O., & Risquez, A. (2024). Exploring adaptive learning, learner–content interaction and student performance in undergraduate economics classes. *Computers & Education*. https://doi.org/10.1016/j.compedu.2024.105047

*Kaïss, W., Mansouri, K., & Poirier, F. (2023). Effectiveness of an adaptive learning chatbot on students' learning outcomes based on learning styles. *International Journal of Emerging Technologies in Learning (iJET)*. https://doi.org/10.3991/ijet.v18i13.39329

Kanta, S. (2023). The role of artificial intelligence in personalized learning. *ShodhKosh: Journal of Visual and Performing Arts*. https://doi.org/10.29121/shodhkosh.v5.i7.2024.4810

Kaouni, M., Lakrami, F., & Labouidya, O. (2023). The design of an adaptive e-learning model based on artificial intelligence for enhancing online teaching. *International Journal of Emerging Technologies in Learning (iJET)*, *18*(6), 202–219. https://doi.org/10.3991/ijet.v18i06.35839

Katiyar, P., Awasthi, V., Pratap, R., Mishra, K., Shukla, N., Singh, R., & Tiwari, M. (2024). AI-driven personalized learning systems: Enhancing educational effectiveness. *Educational Administration: Theory and Practice*. https://doi.org/10.53555/kuey.v30i5.4961

*Kölekar, S. V., Pai, R. M., & Manohara Pai M. (2018). Rule based adaptive user interface for adaptive e-learning system. *Education and Information Technologies*. https://doi.org/10.1007/s10639-018-9788-1

*Laak, K., & Aru, J. (2024). AI and personalized learning: Bridging the gap with modern educational goals. *arXiv*. https://doi.org/10.48550/arxiv.2404.02798

*Lee, D., Huh, Y., Lin, C.-Y., Reigeluth, C. M., & Lee, E. (2021). Differences in personalized learning practice and technology use in high- and low-performing learner-centered schools in the United States. *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-021-09937-y

Lepri, B., Oliver, N., & Pentland, A. (2021). Ethical machines: the human-centric use of artificial intelligence. *iScience*, *24*(3), 102249. https://doi.org/10.1016/j.isci.2021.102249

*Leshchenko, M., Lavrysh, Y., Halatsyn, K., Feshchuk, A., & Prykhodko, D. (2023). Technology-enhanced personalized language learning: Strategies and challenges. *International Journal of Emerging Technologies in Learning (iJET)*. https://doi.org/10.3991/ijet.v18i13.39905

*Li, L. (2023a). Classroom teaching decision-making optimization for students' personalized learning needs. *International Journal of Emerging Technologies in Learning*. https://doi.org/10.3991/ijet.v18i09.40233

*Li, Z. (2023b). AI-assisted emotion recognition: Impacts on mental health education and learning motivation. *International Journal of Emerging Technologies in Learning, 18*(24), 34–48. https://doi.org/10.3991/ijet.v18i24.45645

*Li, K. C., & Wong, B.T.-M. (2020). Features and trends of personalised learning: A review of journal publications from 2001 to 2018. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2020.1811735
*Liu, L. (2024). Impact of AI gamification on EFL learning outcomes and nonlinear dynamic motivation: Comparing adaptive learning paths, conversational agents, and storytelling. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-13296-5
*Luo, G., Gu, H., Dong, X., & Zhou, D. (2025). HA-LPR: A highly adaptive learning path recommendation. *Education and Information Technologies*. https://doi.org/10.1007/s10639-025-13395-x
*Martin, F., Chen, Y., Moore, R. L., & Westine, C. D. (2020a). Systematic review of adaptive learning research designs, context, strategies, and technologies from 2009 to 2018. *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-020-09793-2
*Martin, F., Dennen, V. P., & Bonk, C. J. (2020b). A synthesis of systematic review research on emerging learning environments and technologies. *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-020-09812-2
*Mejeh, M., & Rehm, M. (2024). Taking adaptive learning in educational settings to the next level: Leveraging natural language processing for improved personalization. *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-024-10345-1
*Mirata, V., Hirt, F., Bergamin, P., & van der Westhuizen, C. (2020). Challenges and contexts in establishing adaptive learning in higher education: Findings from a Delphi study. *International Journal of Educational Technology in Higher Education*. https://doi.org/10.1186/s41239-020-00209-y
*Mousavinasab, E., Zarifsanaiey, N., Kalhori, S. R. N., Rakhshan, M., Keikha, L., & Saeedi, M. G. (2018). Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2018.1558257
*Murad, D. F., Heryadi, Y., Muhamad, S., & Budiharto, W. (2020). Personalization of study material based on predicted final grades using multi-criteria user–collaborative filtering recommender system. *Education and Information Technologies*. https://doi.org/10.1007/s10639-020-10238-9
*Mustafa, M. Y., Tlili, A., Lampropoulos, G., Huang, R., Jandrić, P., Zhao, J., & Saqr, M. (2024). A systematic review of literature reviews on artificial intelligence in education (AIED): A roadmap to a future research agenda. *Smart Learning Environments, 11*(1), 59.
*Nguyen, H., Trung, K. D., Duc, L. N., Hoang, L. D., Ba, P. T., & Nguyen, V. A. (2023). A model to create a personalized online course based on the student's learning styles. *Education and Information Technologies, 29*, 571–593. https://doi.org/10.1007/s10639-023-12287-2
Okoli, C. (2015). A guide to conducting a standalone systematic literature review. *Communications of the Association for Information Systems, 37*(1), 879–910. https://doi.org/10.17705/1CAIS.03743
Romi, I. M. (2023). An adaptive e-learning systems success model. *International Journal of Emerging Technologies inLearning (iJET)*, *18*(18), 177–191. https://doi.org/10.3991/ijet.v18i18.42929
*Schmid, R., & Petko, D. (2019). Does the use of educational technology in personalized learning environments correlate with self-reported digital skills and beliefs of secondary-school students? *Computers & Education*. https://doi.org/10.1016/j.compedu.2019.03.006
*Schmid, R., Pauli, C., & Petko, D. (2022). Examining the use of digital technology in schools with a school-wide approach to personalized learning. *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-022-10167-z
*Shemshack, A., & Spector, J. M. (2020). A systematic literature review of personalized learning terms. *Smart Learning Environments, 7*, 17. https://doi.org/10.1186/s40561-020-00140-9
*Smyrnova-Trybulska, E., Morze, N., & Varchenko-Trotsenko, L. (2022). Adaptive learning in university students' opinions: Cross-border research. *Education and Information Technologies*. https://doi.org/10.1007/s10639-021-10830-7
Taşkın, M. (2025). Artificial intelligence in personalized education: Enhancing learning outcomes through adaptive technologies and data-driven insights. *Human Computer Interaction*. https://doi.org/10.62802/ygye0506
*Troussas, C., Chrysafiadi, K., & Virvou, M. (2020). Personalized tutoring through a stereotype student model incorporating a hybrid learning style instrument. *Education and Information Technologies*. https://doi.org/10.1007/s10639-020-10366-2
*Van Schoors, R., Elen, J., Raes, A., & Depaepe, F. (2021). An overview of 25 years of research on digital personalised learning in primary and secondary education: A systematic review of conceptual and methodological trends. *British Journal of Educational Technology*. https://doi.org/10.1111/bjet.13148
*Vanbecelaere, S., Van Schoors, R., Bhatt, S., Rajagopal, K., Debeer, D., & Depaepe, F. (2023). Evaluating teachers' perceptions and use of a portal for digital personalised learning: A multiple case study in Flanders. *Education and Information Technologies*. https://doi.org/10.1007/s10639-023-11931-1
*Walter, Y. (2024). Embracing the future of artificial intelligence in the classroom: The relevance of AI literacy, prompt engineering, and critical thinking in modern education. *International Journal of Educational Technology in Higher Education*. https://doi.org/10.1186/s41239-024-00448-3
*Wan, H., & Yu, S. (2020). A recommendation system based on an adaptive learning cognitive map model and its effects. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2020.1858115
Wang, S., Christensen, C., Cui, W., Tong, R., Yarnall, L., Shear, L., & Feng, M. (2020). When adaptive learning is effective learning: Comparison of an adaptive learning system to teacher-led instruction. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2020.1808794
*Wang, F., Han, M., & Wei, P. (2022). A dynamic learning interest model for a personalized learning requirement analysis of college students. *International Journal of Emerging Technologies in Learning (iJET)*. https://doi.org/10.3991/ijet.v17i23.35937
*Wang, X., Maeda, Y., & Chang, H.-H. (2024). Development and techniques in learner model in adaptive e-learning systems: A systematic review. *Computers & Education*. https://doi.org/10.1016/j.compedu.2024.105184

*Xie, H., Chu, H.-C., Hwang, G.-J., & Wang, C.-C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers & Education*. https://doi.org/10.1016/j.compedu.2019.103599

Xu, X. (2025). AI optimization algorithms enhance higher education management and personalized teaching through empirical analysis. *Scientific Reports*. https://doi.org/10.1038/s41598-025-94481-5

*Xu, Z., Wijekumar, K., Ramirez, G., Hu, X., & Irey, R. (2019). The effectiveness of intelligent tutoring systems on K–12 students' reading comprehension: A meta-analysis. *British Journal of Educational Technology*. https://doi.org/10.1111/bjet.12758

*Xu, X., Li, Z., Cheong, W., Hong, H., Xu, X., Zhang, Y., & Xu, X. (2024). Effects and side effects of personal learning environments and personalized learning in formal education. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-12685-0

*Yang, H., & Alabool, H. M. (2022). Application of exercise-correlated knowledge proficiency tracing model based on multiple learning objectives in English teaching curriculum resources. *International Journal of Emerging Technologies in Learning (iJET)*. https://doi.org/10.3991/ijet.v17i24.35417

*Yu, J. H., & Chauhan, D. (2024). Trends in NLP for personalized learning: LDA and sentiment analysis insights. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-12988-2

Yu, H., & Guo, Y. (2023). Generative artificial intelligence empowers educational reform: Current status, issues, and prospects. *Frontiers in Education*. https://doi.org/10.3389/feduc.2023.1183162

*Zayet, T. M. A., Ismail, M. A., Almadi, S. H. S., Zawia, J. M. H., & Nor, A. M. (2022). What is needed to build a personalized recommender system for K–12 students' e-learning? Recommendations for future systems and a conceptual framework. *Education and Information Technologies*. https://doi.org/10.1007/s10639-022-11489-4

*Zhang, L., Zeng, X., & Lv, P. (2022). Higher education-oriented recommendation algorithm for personalized learning. *International Journal of Emerging Technologies in Learning*. https://doi.org/10.3991/ijet.v17i16.33179

*Zhao, J. (2025). Advancing English language education: A mixed-methods analysis of AI-driven tools' impact on engagement, personalization, and learning outcomes. *Education and Information Technologies*. https://doi.org/10.1007/s10639-025-13560-2

*Zheng, Y., Wang, D., Zhang, J., Li, Y., Xu, Y., Zhao, Y., & Zheng, Y. (2024). A unified framework for personalized learning pathway recommendation in e-learning contexts. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-13045-8

*Zine, O., Derouich, A., & Talbi, A. (2019). IMS compliant ontological learner model for adaptive e-learning environments. *International Journal of Emerging Technologies in Learning (iJET)*. https://doi.org/10.3991/ijet.v14i16.10682

*Zou, D., Wang, M., Xie, H., Cheng, G., Lee, F., Lee, L.-K., Wang, F. L., & Lee, K. (2020). A comparative study on linguistic theories for modeling EFL learners: Facilitating personalized vocabulary learning via task recommendations. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2020.1789178

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.