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AI–Supported Personalized Learning in Education: A Systematic Review and Human-Centered Conceptual Framework (2019–2026)

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ABSTRACT

Objective: The present systematic review synthesizes peer-reviewed research published between 2019 and 2026 to examine how personalized learning has been conceptualized, implemented, and redefined within AI-supported educational environments.

Methods: Following the PRISMA 2020 guidelines, relevant studies were systematically identified across four major academic databases (Scopus, Web of Science, IEEE Xplore, and ERIC) and analyzed to explore conceptual definitions, technological innovations, pedagogical applications, ethical considerations, and emerging research directions. In addition to synthesizing established evidence, the review incorporates recent advances in generative AI, learning analytics, explainable AI, multimodal learning environments, and human–AI collaboration, thereby extending previous reviews and providing a more contemporary understanding of AI-enhanced personalized learning.

Results: The findings demonstrate that personalized learning is increasingly evolving toward intelligent, adaptive ecosystems in which educators and AI systems operate as complementary partners to support individualized learning while maintaining human oversight and pedagogical integrity. Despite substantial technological progress, persistent challenges (including conceptual ambiguity, algorithmic bias, data privacy, transparency, equitable implementation, and teacher preparedness) continue to limit widespread adoption and effectiveness. Building upon the synthesized evidence, this review proposes an *Integrated Human-Centered AI Personalized Learning Framework* that unifies the essential pedagogical, technological, and ethical dimensions of personalized learning into a comprehensive conceptual model.

Conclusion: Overall, AI-supported personalized learning has progressed from an emerging educational innovation to a strategically important component of contemporary education. Its future success will depend not only on advances in AI but also on the quality of collaboration among educators, learners, institutions, and policymakers.

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1. Introduction

Artificial intelligence (AI) has become one of the most influential forces in contemporary education, changing how teaching, learning, assessment, and academic support are designed and delivered (Isaee & Barjesteh, 2026a, 2026b). Advances in machine learning, natural language processing, generative AI, and learning analytics now allow learning environments to adjust instruction to learners' cognitive, behavioral, and motivational characteristics, and they have accelerated the move from standardized instruction toward flexible, data-informed, learner-centered ecosystems (Castro et al., 2024; Mustafa et al., 2024).

Within this transformation, personalized learning has become a central paradigm. Instead of treating learners as a homogeneous group, it adapts content, pathways, assessment, pacing, and support to individual needs, interests, abilities, and prior knowledge (Schmid et al., 2022; Xie et al., 2019). Yet its conceptual boundaries remain blurred. Terms such as adaptive learning, individualized instruction, customized learning, intelligent tutoring systems, and digital personalized learning are used interchangeably despite differing in pedagogical assumptions, degrees of automation, and theoretical foundations, which complicates comparison across studies and the development of coherent theory (Shemshack & Spector, 2020; Wang et al., 2025; Xie et al., 2019).

Generative AI has intensified these issues. Conversational agents, automated feedback, content generation, and predictive analytics extend personalization well beyond earlier adaptive systems, while raising questions of transparency, privacy, fairness, explainability, and human agency (Bayly-Castaneda et al., 2024; García-López & Trujillo-Liñán, 2025; Laak & Aru, 2024). In response, scholarship increasingly positions AI as a collaborative partner rather than a replacement for educators (Barjesteh & Isaee, 2026; Mustafa et al., 2024; Walter, 2024). Previous reviews have clarified terminology (Shemshack & Spector, 2020) and mapped AI applications and adaptive technologies (Bayly-Castaneda et al., 2024; Hashim et al., 2022; Isaee et al., 2026; Mustafa et al., 2024; Risdianto et al., 2025). Few, however, connect terminology, pedagogy, technology, ethics, and the changing roles of teachers and learners in a single human-centered model. The two subsections below specify the problem this gap creates and the objectives the present review pursues.

The present review addresses this gap in three ways. It applies a systematic procedure to identify and appraise studies published between 2019 and 2026, a period that spans both the consolidation of adaptive and analytics-based personalization and the arrival of generative AI. It treats personalization as a continuously negotiated process rather than a fixed technological outcome: learner needs, pedagogical priorities, institutional conditions, and AI capabilities change over time, so effective personalization requires ongoing evaluation and adjustment rather than the permanent

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assignment of learners to algorithmically determined pathways. And it derives a conceptual framework directly from the synthesized evidence so that each of its dimensions can be traced to specific studies. The intended audience includes researchers, educators, educational technology developers, and policymakers who need a coherent basis for the next generation of personalized learning.

1.1 Statement of the Problem

Three interrelated problems motivate this study. The first is conceptual fragmentation. Personalized, adaptive, individualized, and customized learning are defined inconsistently, so findings accumulate without a shared vocabulary (Shemshack & Spector, 2020). In much of the literature, human-centered and ethical considerations are discussed alongside, rather than within, analyses of personalization (see Section 2.4). The second problem is an uneven and technology-centered evidence base. Internationally, a meta-synthesis of 143 AI-in-education reviews found that most research originates in China and the United States, concentrates on higher education, and gives little attention to special education and to stakeholders other than teachers and students (Mustafa et al., 2024). Large-scale longitudinal evidence on personalized learning has likewise concentrated on learners aged eleven and above, leaving younger learners comparatively under-studied (Ackermans et al., 2025). A review of 102 studies further concluded that AI-enabled personalization depends on educators' competencies and on resolving ethical concerns such as data privacy and bias (Castro et al., 2024).

The third problem is limited contextual evidence from settings such as Iran. A study of 400 Iranian undergraduates in virtual universities reported that AI literacy was significantly associated with academic well-being and educational attainment (Xiao et al., 2024), which shows that learners' capacity to use AI critically shapes its benefits. A mixed-methods study of Iranian pre-service EFL teachers, in turn, found uneven AI literacy, stronger in foundational skills than in advanced competencies, and called for targeted teacher education (Tusi Nasrabadi et al., 2025). Together, these national findings suggest that effective personalization cannot be assumed from technology alone. It depends on the preparedness of both teachers and learners.

Taken together, the field lacks an evidence-grounded conceptual model that integrates technological, pedagogical, human, and ethical dimensions of AI-supported personalized learning. Without such a model, researchers cannot compare studies on common terms, and practitioners cannot judge when and how personalization should be implemented responsibly.

These problems have practical consequences. Conceptual ambiguity makes it hard to decide which approach a given study evaluates and whether its results transfer to other settings. Technology-centered evidence encourages adoption decisions based on what a system can do rather than on pedagogical fit. And the scarcity of contextual evidence leaves institutions in settings such

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as Iran to rely on findings produced elsewhere, under different infrastructural, linguistic, and policy conditions. A framework that makes the human and ethical conditions of personalization explicit is therefore needed for research and for responsible implementation alike.

1.2 Objectives of the Study

The overall aim of this study is to synthesize peer-reviewed research published between 2019 and 2026 on AI-supported personalized learning and to develop an evidence-grounded, human-centered conceptual framework. The specific objectives are to:

(1) clarify how personalized learning has been conceptualized and distinguished from related approaches in AI-supported environments; (2) identify the AI technologies used to support personalization and describe how they have evolved; (3) synthesize the educational benefits, implementation challenges, and ethical issues reported in the literature; and (4) derive from this evidence an Integrated Human-Centered AI Personalized Learning (HCAI-PL) Framework and show transparently how each of its dimensions is supported by the reviewed studies.

These objectives correspond to four research questions:

RQ1, how has AI been applied to support personalized learning across educational contexts?

RQ2, which AI technologies have been most frequently adopted, and how have they evolved?

RQ3, what benefits, challenges, and ethical issues are reported?

RQ4, how can the collective evidence be synthesized into an integrated conceptual framework that supports future research and practice?

2. Theoretical Background

2.1 Evolution of Personalized Learning in the Age of AI

The idea of adapting instruction to learners' abilities, interests, and pace predates digital technology. Standardized curricula supported large-scale education but left little room for differences in prior knowledge, motivation, and learning speed; learner-centered and differentiated approaches gradually challenged this uniformity (Bernacki et al., 2021; Schmid & Petko, 2019). Educational data mining, learner modeling, and learning analytics then allowed platforms to analyze learner interactions, identify difficulties, recommend resources, and adjust pathways (Martin et al., 2020a, 2020b; Wang et al., 2025). Machine learning, natural language processing, and generative AI have since enabled explanations, materials, and feedback to be generated and adapted dynamically for both students and teachers (Bayly-Castaneda et al., 2024; García-López & Trujillo-Liñán, 2025; Walter, 2024).

Personalization nevertheless remains more than a technical process. Teachers interpret AI recommendations, design meaningful learning experiences, and support learners' emotional and

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social development (Hobert & Berens, 2024; Lee et al., 2021; Walter, 2024), and contemporary systems increasingly address engagement, motivation, and autonomy in addition to performance (Karbakhsh Ravari, Nakhaee Ravari, & Rabani, 2025; Lepri et al., 2021; Mustafa et al., 2024). The evolution of the field is therefore best described as a movement from instructional adjustment toward socio-technical ecosystems, which creates both opportunities and new ethical and implementation challenges.

This trajectory also changes what personalization means. In early digital systems it meant selecting among predefined paths; in AI-supported systems the technology may infer learner states, generate content, and adapt continuously. As decision-making shifts toward algorithms, the question of who controls the adaptation, whether the learner, the teacher, or the system, becomes central (Bernacki et al., 2021). This question is taken up in Section 2.3 and in the framework presented in Section 5.

2.2 Conceptual Boundaries of Personalized Learning and Related Approaches

Personalized learning aligns instruction with learners' needs, interests, abilities, and goals, allowing flexibility in activities, strategies, assessment, and pace while encouraging learners to take an active role (Bernacki et al., 2021; Schmid & Petko, 2019). Individualized learning also addresses learner differences but primarily varies the pace at which students pursue common objectives (Shemshack & Spector, 2020). Adaptive learning introduces data-driven, often AI-based, decision-making that modifies content, difficulty, feedback, or pathways in response to real-time learner data (Martin et al., 2020a). Differentiated instruction refers to teacher-led modification of methods, activities, or assessment for groups of learners; technology may assist, but adaptation remains under the teacher's control (Schmid & Petko, 2019). AI-supported personalized learning, as used in this review, integrates intelligent technologies with learner-centered pedagogy so that adaptation is data-informed yet guided by human expertise. Table 1 summarizes these distinctions.

Table 1. Comparison of major learner-centered instructional approaches

Approach	Primary focus	Degree of AI support	Role of the teacher
Personalized learning	Individual needs, interests, goals, and learning pathways	Moderate to high	Designs and supervises personalized learning
Individualized learning	Learning pace and progression	Low	Determines learning sequence and monitors progress
Adaptive learning	Automatic adjustment based on learner data	High	Interprets AI recommendations and supports learners
Differentiated instruction	Adapting instruction for groups of learners	Low to moderate	Leads instructional adaptation
AI-supported personalized learning	Integration of AI with pedagogy, learner agency, and ethics	High	Collaborates with AI while retaining educational responsibility

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As Table 1 shows, the approaches differ mainly in who adapts instruction and how much of the adaptation is automated. Individualized learning and differentiated instruction place the decisions with the teacher, adaptive learning delegates much of the decision-making to computational models, and personalized learning is the broader goal to which all of these may contribute. AI-supported personalized learning is distinguished less by any single technology than by the combination of data-driven adaptation, learner-centered pedagogy, and human oversight. This reading is used throughout the review to decide which studies fall within scope and how their findings are interpreted.

2.3 Human-Centered AI in Education

Human-centered AI (HCAI) holds that intelligent systems should be designed around human values, needs, and capabilities. In education this means enhancing learning while preserving learner agency, teacher autonomy, transparency, and ethical responsibility, and treating AI as a supportive partner rather than an independent decision-maker (Isaee & Barjesteh, 2025; Lepri et al., 2021; Mustafa et al., 2024; Yin et al., 2024; Walter, 2024). Three principles are especially relevant to personalization. Human agency means that learners and educators keep control over important educational decisions, and AI proposes options that they can question, modify, or reject. Transparency and explainability allow users to understand why a recommendation is made. Fairness and responsibility require attention to bias, unequal access, and the risks of educational data (Yin et al., 2024; Walter, 2024). These principles matter more with generative AI, which introduces concerns about accuracy, privacy, academic integrity, and over-reliance (García-López & Trujillo-Liñán, 2025; Walter, 2024). Where decision authority is distributed in this way, personalization is less likely to become algorithmic control.

Importantly, a human-centered stance does not mean limiting automation. It means specifying which decisions the system may take autonomously (for example, sequencing practice items), which require teacher judgment (for example, interpreting a risk prediction), and which belong to learners (for example, setting goals), and making these boundaries visible and revisable. This distinction underpins the dimensions of the framework proposed in Section 5.

2.4 Research Gap and Rationale for the HCAI-PL Framework

Existing research has advanced adaptive systems, intelligent tutoring, learning analytics, recommender systems, and generative AI, but it remains fragmented. Technical studies emphasize prediction accuracy, adaptive algorithms, and automated feedback (Martin et al., 2020a; Troussas et al., 2021; Wang et al., 2023); pedagogical studies examine engagement, self-regulation, and effectiveness in specific settings (Bernacki et al., 2021; Lee et al., 2021); and ethical work addresses transparency, fairness, privacy, and governance (García-López & Trujillo-Liñán, 2025; Yin et al., 2024). These strands are rarely analyzed together, and teachers, learners, and institutions

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are typically discussed as complementary conditions rather than as core components of design (Hobert & Berens, 2024; Lee et al., 2021).

This review responds by deriving a framework from the included evidence rather than from an a priori theory. The framework integrates five dimensions: AI technologies, pedagogical design, learner agency, teacher expertise, and ethical governance. It is intended as a dynamic system in which a change in one dimension, such as a new AI capability, may require adjustment in the others. How the dimensions were derived and what evidence supports each is reported in Sections 3.5 and 5.

3. Materials and Methods

3.1 Research Design and Reporting

A systematic review with narrative and thematic synthesis was conducted in accordance with the PRISMA 2020 guidelines (Page et al., 2021). This design was appropriate because the literature is large and heterogeneous in contexts, technologies, methods, and outcomes, and a transparent, replicable procedure reduces selection bias. The review was guided by the four research questions stated in Section 1.2. Because the aim extends to conceptual integration, the review combines evidence synthesis with the derivation of a framework from the synthesized themes.

Unlike a narrative review, a systematic review follows predefined procedures for identifying, selecting, appraising, and synthesizing studies, which improves transparency and allows other researchers to replicate the search. Many earlier reviews in this field have catalogued AI applications or reported outcomes; the present review additionally asks how technological, pedagogical, human, and ethical components interact within a broader educational ecosystem, and it designs its procedures, particularly the extraction fields and the thematic synthesis, to support that question.

3.2 Search Strategy

Four databases were searched: Scopus, Web of Science Core Collection, IEEE Xplore, and ERIC. Scopus and Web of Science provide broad multidisciplinary coverage, IEEE Xplore indexes intelligent-systems and learning-analytics research that other databases may miss, and ERIC specializes in educational research. The search covered January 2019 to June 2026, a window chosen because research on AI-supported personalization expanded rapidly after 2019 and because large language models and generative AI after 2022 introduced developments not adequately covered by earlier reviews. The representative search string was:

("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "learning analytics" OR "educational data mining" OR "generative AI" OR "large language model" OR "ChatGPT" OR "intelligent tutoring system*") AND ("personalized learning" OR "personalised*

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learning" OR "adaptive learning" OR "individualized instruction" OR "individualised instruction" OR "customized learning" OR "customised learning")

Syntax was adapted to each database; for example, ERIC controlled vocabulary was used where appropriate, whereas Scopus and Web of Science relied on title, abstract, and keyword searches. Pilot searches checked that well-known studies were retrieved, and terms such as generative AI, large language models, and ChatGPT were added as a result. Records were exported to reference-management software and de-duplicated before screening. Backward and forward citation searching of key reviews and highly relevant empirical studies supplemented the database search. Databases, search dates, terms, eligibility criteria, and screening decisions were documented to support reproducibility.

Other sources, such as Google Scholar or ProQuest, were not searched, and grey literature and non-English publications were not sought, reflecting the decision to focus on peer-reviewed evidence. These choices are acknowledged as limitations in Section 7.

3.3 Study Selection

Eligibility criteria were defined before the search. Studies were included if they examined AI applied to support personalized learning in formal or informal educational settings and provided empirical evidence, systematic synthesis, or a substantial conceptual contribution; if they were peer-reviewed journal articles or conference papers; and if they were published in English between January 2019 and June 2026. Editorials, opinion pieces, book reviews, dissertations, theses, magazine articles, unpublished manuscripts, studies of educational technology without AI, and papers on AI algorithms without an educational connection were excluded.

Titles and abstracts were screened first. Records that appeared relevant, or whose eligibility was unclear, were assessed in full text, and the main reason for each exclusion was recorded. Ambiguous cases were resolved by returning to the full text and the review objectives rather than relying on keywords or titles. Twenty-six studies were retained for synthesis. The selection process is shown in Figure 1.

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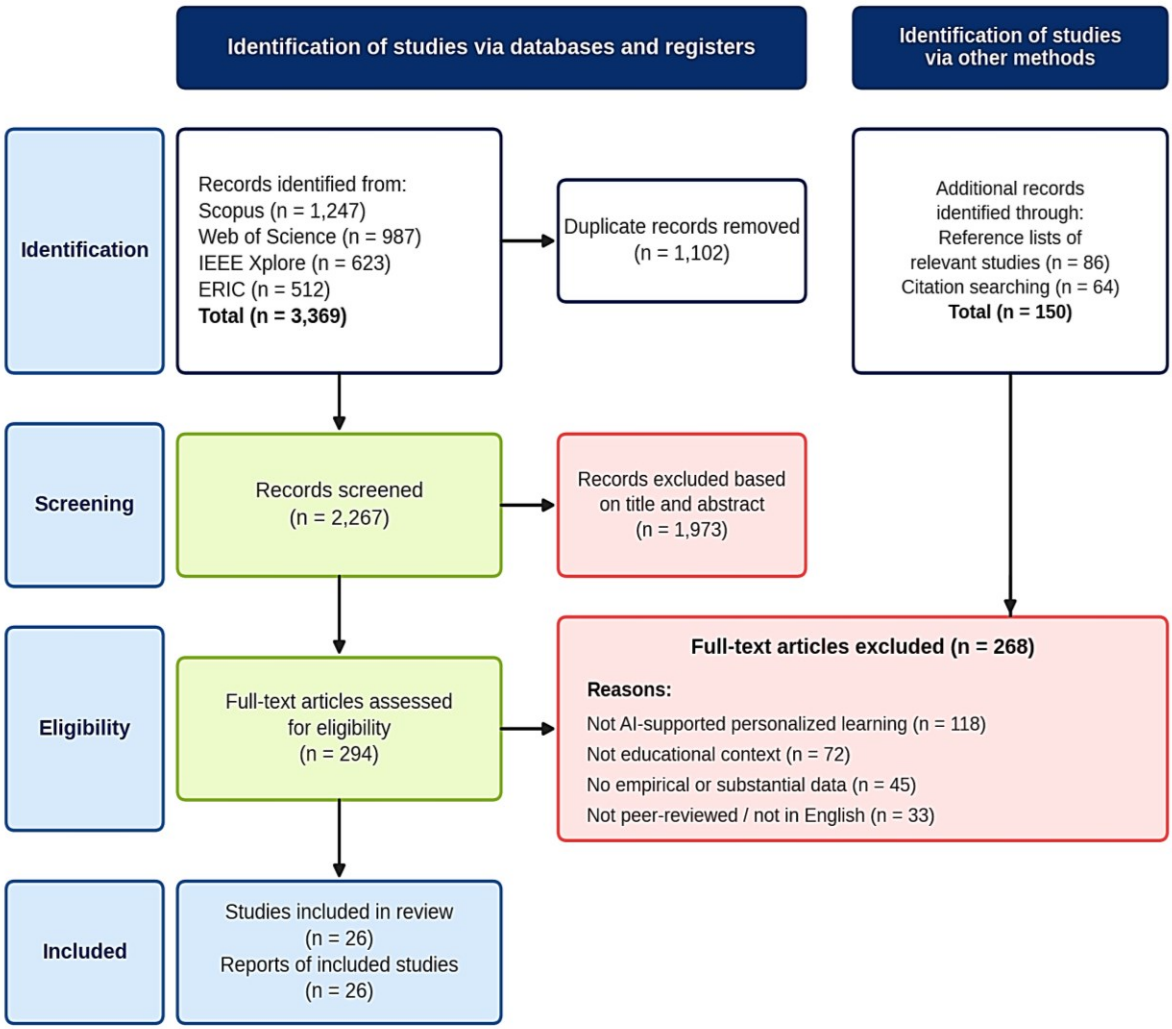


Figure 1. PRISMA 2020 flow diagram of the study selection process

3.4 Data Extraction and Quality Assessment

A structured extraction protocol developed before the analysis was used to record bibliographic details, educational context, AI technology, research design, sample, data collection and analysis methods, and principal findings, with emphasis on benefits, challenges, and ethical considerations. Uncertainties were resolved by returning to the full text.

Extraction concentrated on recurring patterns rather than isolated results, so that evidence from different settings and designs could be examined together. The extracted information was reviewed repeatedly during the analysis to ensure that it accurately reflected the original authors' findings, and the resulting table of study characteristics is presented as Table 2.

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Because the included studies comprised quantitative, qualitative, mixed-methods, review, and conceptual work, no single risk-of-bias instrument was appropriate. Each study was instead appraised against five common indicators: clarity of objectives, appropriateness of methodology, transparency of data collection and analysis, coherence between findings and evidence, and relevance to the review. The appraisal was used to weight the interpretation of findings, with studies of limited methodological detail interpreted more cautiously, rather than to exclude studies or compute numerical scores.

The indicators were read in a design-sensitive way. For evidence syntheses, attention was given to the transparency of search and synthesis procedures; for empirical studies, to the adequacy of the design, sample, and measures; and for conceptual papers, to the coherence of the argument and its grounding in the literature. Findings from studies with limited methodological detail are presented with corresponding caution in Section 4.

3.5 Data Synthesis and Framework Development

Synthesis followed four stages. First, each study was described individually (focus, context, technology, design, findings). Second, studies were compared to identify recurring patterns and to separate widely supported conclusions from context-specific ones; contradictory findings were retained and interpreted in light of context rather than discarded. Third, recurring patterns were organized into thematic categories (adaptive personalization, intelligent feedback and tutoring, learning analytics and prediction, generative AI and interactive learning, and human-centered implementation; Table 3).

Throughout the synthesis, contradictory findings were examined alongside consistent ones. Where studies reached different conclusions about the effectiveness of personalization, about learner motivation, or about the role of teachers, differences were interpreted in terms of educational context, learner age, the type of technology, and the way personalization was implemented. Conclusions were drawn from patterns that recurred across studies rather than from isolated results, and alternative interpretations were considered before broader claims were made. This approach limits overgeneralization and keeps the framework anchored in the available evidence.

The fourth stage derived the HCAI-PL Framework from these themes. Themes were grouped into dimensions by conceptual affinity and retained as framework dimensions when they were supported by more than one included study and when the literature described them as shaping the effectiveness of personalization rather than as incidental conditions. This procedure yielded five dimensions: AI technologies, pedagogical design, learner agency, teacher expertise, and ethical governance. Section 5 reports the evidence supporting each dimension (Table 4). The framework is therefore a conceptual synthesis grounded in the reviewed studies rather than a new theory, and

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its proposed relationships are presented as propositions for empirical testing, not as established findings.

4. Results

4.1 Characteristics of the Included Studies

The 26 included studies are listed in Table 2. Evidence syntheses (systematic and scoping reviews, meta-analyses, and a review of reviews) account for 13 of the 26 studies, primary empirical studies (including a Delphi, a case, and a design study) for 11, and conceptual or perspective papers for 2. Roughly half of the evidence base is therefore secondary, which strengthens its breadth but limits what can be said about the direct effects of specific AI systems. Higher education was the most frequent single context (10 studies), followed by school-level education (6 studies: primary, secondary, or K–12); the remaining studies addressed multiple or general contexts.

Table 2. Characteristics of the included studies (n = 26)

ID	Study	Context	AI application	Design	Main contribution
S1	Xie et al. (2019)	Technology-enhanced learning	Adaptive/personalized learning	Systematic review	Mapped trends in adaptive and personalized learning research (2007–2017).
S2	Xu et al. (2019)	K–12	Intelligent tutoring systems	Meta-analysis	Examined ITS effectiveness for reading comprehension.
S3	Martin et al. (2020a)	Mostly higher education	Adaptive learning systems	Systematic review	Reviewed designs, contexts, strategies, and technologies (2009–2018).
S4	Martin et al. (2020b)	Emerging learning environments	Educational technologies	Review of reviews	Synthesized systematic reviews on emerging learning technologies.
S5	Mirata et al. (2020)	Higher education	Adaptive learning	Delphi study	Identified contextual challenges in establishing adaptive learning.
S6	Murad et al. (2020)	Higher education	Recommender system	Empirical study	Personalized study material using predicted grades and collaborative filtering.
S7	Shemshack & Spector (2020)	General	Personalized learning terms	Systematic review	Clarified terminology and dimensions of personalized learning.
S8	Troussas et al. (2021)	Higher education	Intelligent tutoring	Empirical study	Personalized tutoring via a stereotype student model and learning-style instrument.
S9	Wan & Yu (2023)	Higher education	Adaptive recommendation	Empirical study	Recommendations based on an adaptive learning cognitive map.
S10	Wang et al. (2023)	Higher education	Adaptive learning system	Comparative study	Compared adaptive learning with teacher-led instruction.
S11	Schmid & Petko (2019)	Secondary	Digital personalized learning	Survey (SEM)	Linked technology use in personalized environments to students' digital skills and ICT beliefs.
S12	Van Schoors et al. (2021)	Primary and secondary	Digital personalized learning	Systematic review	Reviewed 25 years of conceptual and methodological trends.

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ID	Study	Context	AI application	Design	Main contribution
S13	Bernacki et al. (2021)	Multiple levels	Personalized learning	Systematic review	Analyzed by whom, to what, how, and why learning is personalized.
S14	Lee et al. (2021)	K–12 schools	Technology for personalized learning	National survey	Compared practices and technology use in high- and low-performing schools.
S15	Schmid et al. (2022)	Lower secondary	Technology in personalized schools	Multiple-case study	Examined school-wide technology use for personalized learning.
S16	Alé-Ruiz et al. (2024)	Higher education	Digital ecosystems	Empirical study	Examined academic engagement and management of personalized active learning.
S17	Barbosa et al. (2024)	Higher education (computing)	Adaptive learning	Scoping review	Mapped adaptive learning research in computer science education.
S18	Hobert & Berens (2024)	Higher education	Chatbot digital tutor	Design study with field evaluation	Designed a tutor mediating among students, assistants, and lecturers.
S19	Yu & Guo (2023)	General	Generative AI	Review/perspective	Discussed status, issues, and prospects of generative AI in education.
S20	Ackermans et al. (2025)	Primary	Personalized learning interventions	Longitudinal study (3 years)	Reported gains in math and spelling; motivation effects not confirmed.
S21	Bayly-Castaneda et al. (2024)	Lifelong learning	AI learning paths	Systematic review	Synthesized AI-based personalized learning-path research.
S22	Castro et al. (2024)	Multiple contexts	AI-supported personalization	Systematic review (102 studies)	Identified drivers of personalized learning and AI's role.
S23	Yin et al. (2024)	General	Fairness in educational AI	Conceptual/review	Addressed fairness, bias, and ethics in educational AI.
S24	Hooshyar et al. (2024)	Higher education	Personalized TEL	Meta-analysis	Found medium effects on cognitive and non-cognitive outcomes.
S25	Mustafa et al. (2024)	Multiple contexts	AI in education	Review of 143 reviews	Mapped the AIED landscape and a future research agenda.
S26	García-López & Trujillo-Liñán (2025)	General	Generative AI	Systematic review	Examined ethical and regulatory challenges of generative AI.

Regarding RQ1, AI has been applied to personalized learning in several recurring ways. In higher education, studies developed or evaluated recommender systems, adaptive recommendation, tutoring based on learner models, and comparisons of adaptive systems with teacher-led instruction (Murad et al., 2020; Troussas et al., 2021; Wan & Yu, 2023; Wang et al., 2023). At school level, the studies concerned intelligent tutoring for reading comprehension, technology use in schools that follow personalized learning policies, and a three-year intervention in primary schools (Ackermans et al., 2025; Lee et al., 2021; Schmid & Petko, 2019; Schmid et al., 2022; Xu et al., 2019). A smaller group examined conversational tutoring and generative AI (Hobert & Berens, 2024; Yu & Guo, 2023), and reviews addressed learning-path recommendation for lifelong learning (Bayly-Castaneda et al., 2024). Taken together, the applications cluster around three functions: adapting content and pathways, providing individualized support and feedback, and informing decisions through data.

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4.2 Publication Trends

Publications peaked in 2024 (n = 8) and 2020 (n = 5), with fewer studies in 2021 (n = 4), 2019 (n = 3), 2023 (n = 3), 2025 (n = 2), and 2022 (n = 1); no study from 2026 met the criteria despite the search window extending to June 2026. One group of studies focused on adaptive learning, intelligent tutoring, recommender systems, and learner modeling (Martin et al., 2020a; Troussas et al., 2021; Wan & Yu, 2023; Wang et al., 2023). A second group adds conversational agents, generative AI, fairness, and ethical governance (García-López & Trujillo-Liñán, 2025; Hobert & Berens, 2024; Yin et al., 2024; Yu & Guo, 2023). Generative AI is nevertheless represented by only a small number of included studies, which suggests that empirical evidence has not kept pace with the technology's adoption. Regarding geography, the included studies do not allow a reliable country-level analysis; the broader literature suggests concentration in China and the United States (Mustafa et al., 2024).

The methodological diversity of the evidence base is both a strength and a constraint. Reviews and meta-analyses provide breadth and allow patterns to be compared across contexts, whereas the primary studies range from surveys and case studies to a three-year longitudinal intervention and a design study with field evaluation. Few studies directly compare matched AI-supported and non-AI conditions, and measures of outcomes differ widely. These features justify a narrative and thematic synthesis rather than a pooled effect estimate, and they explain why the findings below are expressed as recurring patterns and conditions.

4.3 AI Technologies Supporting Personalized Learning

Figure 2 summarizes the main technology categories identified and the outcomes with which they are associated.

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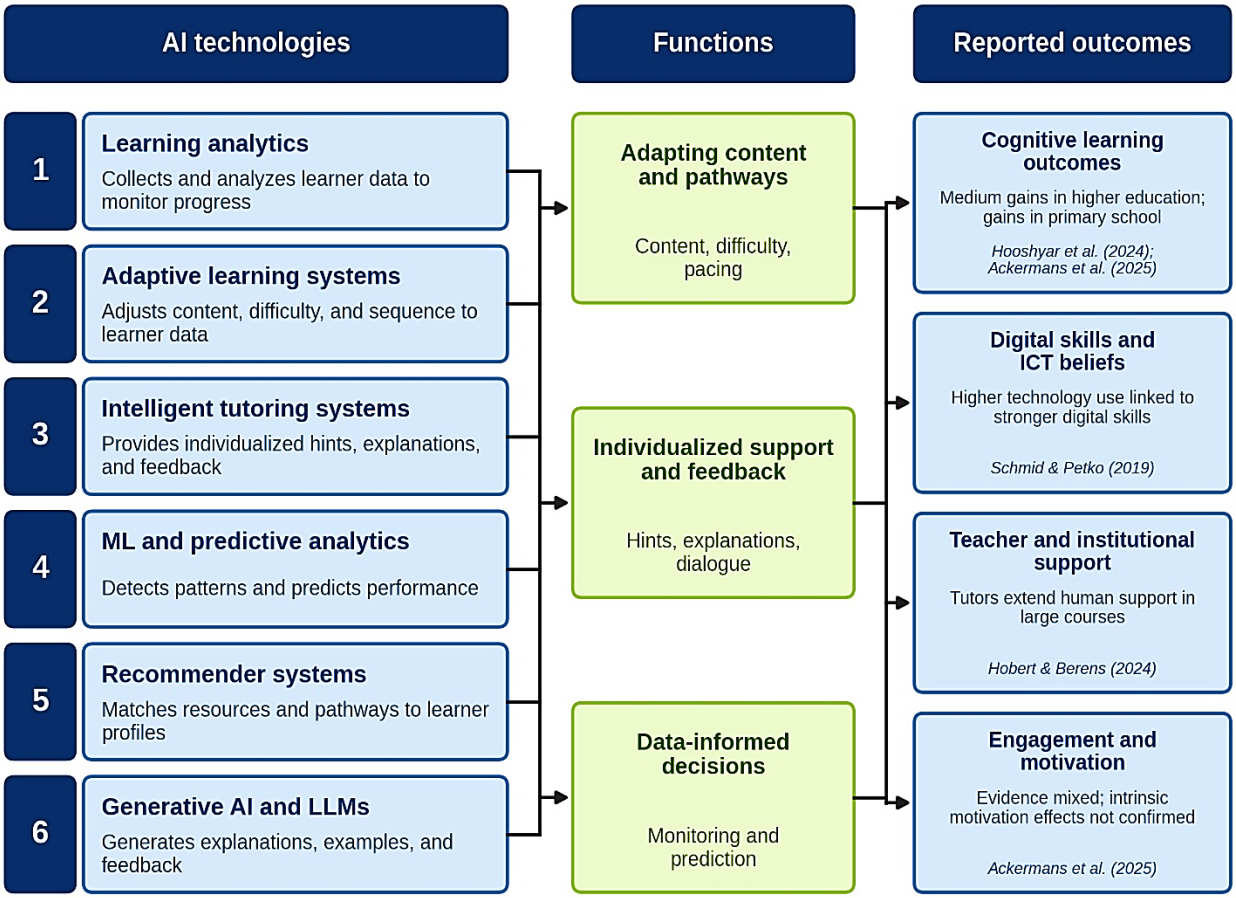


Figure 2. Major AI technologies supporting personalized learning

Adaptive learning systems analyze performance and adjust content, difficulty, or sequence. A review of adaptive learning research from 2009 to 2018 found it concentrated in higher education and computer science, with learning style the most commonly modeled learner characteristic (Martin et al., 2020a), and a later scoping review mapped adaptive learning in computer science education (Barbosa et al., 2024). Evidence on effectiveness is conditional: Wang et al. (2023) compared an adaptive system with teacher-led instruction to examine when adaptive learning is effective, and Bernacki et al. (2021) emphasized that who personalizes, to what, and for what purpose shapes outcomes.

Intelligent tutoring systems (ITS) provide individualized explanations, hints, and feedback. A meta-analysis addressed their effectiveness for K–12 reading comprehension (Xu et al., 2019), and Troussas et al. (2021) developed tutoring based on a stereotype student model and a hybrid learning-style instrument. Learning analytics and machine learning identify learning patterns, predict performance, and support interventions; their value depends on data quality, governance,

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and educators' ability to interpret outputs (Castro et al., 2024). Recommender systems personalize resources and pathways according to learner profiles and prior performance (Murad et al., 2020; Wan & Yu, 2023), and recent work extends this to learning-path recommendation with AI (Bayly-Castaneda et al., 2024).

Machine learning and predictive analytics provide the computational foundation for many of these applications. Rather than functioning as a separate educational technology, they allow systems to detect patterns in learner behavior, estimate future performance, and generate adaptive recommendations; for example, Murad et al. (2020) personalized study materials on the basis of predicted final grades. Predictive capability supports earlier identification of learning difficulties, but its educational value again depends on how teachers and learners use the predictions.

Conversational agents such as the chatbot-based digital tutor of Hobert and Berens (2024) extend individualized support to large classes, and generative AI and large language models can produce explanations, examples, assessments, and feedback in real time and may support learner autonomy outside the classroom (Yu & Guo, 2023). The reviewed literature also stresses accuracy, hallucination, integrity, transparency, and over-reliance as reasons for pedagogical and ethical oversight (García-López & Trujillo-Liñán, 2025; Walter, 2024). Finally, recent work combines several technologies into integrated ecosystems, and technological sophistication should not be treated as a proxy for educational quality: a simple adaptive system aligned with objectives and classroom practice may serve learners better than a more advanced but poorly aligned one.

Two design implications follow. First, because the effectiveness of adaptive and analytics-based systems is conditional on pedagogical alignment and on the competence of the people who use them (Bernacki et al., 2021; Castro et al., 2024), technology selection should begin with learning objectives and classroom practice rather than with available tools. Second, as personalization moves toward conversational and generative systems that produce content rather than select it, the burden of checking accuracy and appropriateness shifts toward teachers and learners, which reinforces the need for AI literacy and for explainable, adjustable systems (García-López & Trujillo-Liñán, 2025; Walter, 2024).

4.4 Educational Outcomes

Evidence from meta-analyses and empirical studies indicates that personalization can improve learning, with important qualifications. A meta-analysis of personalized technology-enhanced learning in higher education reported medium-sized improvements in both cognitive skills and non-cognitive characteristics (Hooshyar et al., 2024). In primary schools, a three-year study of personalized learning interventions found gains in mathematics and spelling but could not confirm theorized effects on metacognitive awareness or intrinsic motivation, and it identified teachers' and students' ICT skills as supporting factors (Ackermans et al., 2025). A national survey in the United

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States found that schools implementing personalized learning practices more thoroughly, and using technology for more functions, achieved higher standardized results (Lee et al., 2021). Reviews of the literature further link personalization with engagement and self-regulated learning but note that benefits depend on learners' self-regulation skills and on instructional design (Bernacki et al., 2021; Castro et al., 2024).

Evidence on engagement and motivation is more mixed than the enthusiasm around personalization suggests. Schmid and Petko (2019) found that greater reported use of digital technologies in open, personalized learning environments was positively related to secondary students' self-reported digital skills and ICT-related beliefs, which indicates a benefit for digital competence rather than for achievement directly. Ackermans et al. (2025), as noted, could not confirm an effect on intrinsic motivation, although they did find that ICT skills supported metacognitive awareness. Alé-Ruiz et al. (2024) approached engagement from the perspective of how personalized active learning is managed in higher education digital ecosystems, which again places weight on management and design rather than on technology alone. Regarding feedback, the evidence in the included studies is largely descriptive: systems such as the tutor of Hobert and Berens (2024) and the tutoring model of Troussas et al. (2021) are designed to deliver individualized support, but rigorous comparisons of feedback quality remain scarce.

Taken together, these studies suggest that benefits are most reliable for cognitive learning outcomes in well-implemented programs, less certain for motivation, and dependent on enabling conditions such as ICT skills, self-regulation, and teacher support. This pattern is consistent with the conditional character of the evidence noted in Section 4.3 and with the propositions advanced in Section 5.

Several studies also point to benefits for teachers and institutions. Hobert and Berens (2024) designed a chatbot-based digital tutor as an intermediary among students, teaching assistants, and lecturers in large-scale courses, illustrating how AI can extend rather than replace human support. Pedagogical design, teacher involvement, learner characteristics, and institutional support recur as conditions that shape these effects (Lee et al., 2021; Mirata et al., 2020; Schmid & Petko, 2019).

4.5 Challenges, Ethical Considerations, and Emerging Trends

Data privacy and security are among the most discussed challenges, because personalization relies on continuous collection of performance, behavioral, and preference data and therefore raises issues of consent, data ownership, and cybersecurity (Castro et al., 2024; Lepri et al., 2021; Yin et al., 2024). Algorithmic bias and fairness are a second concern: models trained on unrepresentative data may produce unequal recommendations, which has prompted calls for fairness evaluation, bias detection, and explainable AI (Yin et al., 2024). Teacher roles and preparedness are a third: AI can automate routine tasks and provide feedback but cannot replace professional judgment and

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socio-emotional support (Hobert & Berens, 2024; Lee et al., 2021), and educator competencies are a recurring condition for adoption (Castro et al., 2024). Institutional and contextual barriers also affect adaptive learning implementation in higher education (Mirata et al., 2020). Academic integrity, AI literacy, and over-reliance on generated content form the fourth cluster of challenges, particularly with generative AI (García-López & Trujillo-Liñán, 2025; Walter, 2024).

Equity cuts across these challenges. Because the broader evidence base is concentrated in particular countries and educational levels and gives little attention to special education (Mustafa et al., 2024), it is uncertain how far findings generalize to under-resourced settings, younger learners, and learners with special needs, and fairness concerns are heightened when training data under-represent such groups (Yin et al., 2024).

Two emerging trends are visible: the integration of multiple AI technologies into unified ecosystems, and growing emphasis on human-centered principles such as agency, transparency, fairness, and governance. Table 3 synthesizes the themes and links them to supporting studies.

Table 3. Thematic synthesis of findings from the included studies

Theme	Supporting studies	Main findings	Implications
Adaptive personalization	Martin et al. (2020a); Wang et al. (2023); Barbosa et al. (2024)	Systems adapt content and pathways to learner data; effectiveness depends on design and context.	Supports flexible trajectories when aligned with pedagogy.
Intelligent feedback and tutoring	Xu et al. (2019); Troussas et al. (2021); Hobert & Berens (2024)	ITS and tutoring agents provide explanations and feedback, extending human support.	Enhances support at scale; requires teacher mediation.
Learning analytics and prediction	Castro et al. (2024); Bernacki et al. (2021); Hooshyar et al. (2024)	Analytics monitor progress; personalization yields medium gains but depends on self-regulation and data governance.	Enables evidence-informed decisions.
Generative AI and interactive learning	Yu & Guo (2023); García-López & Trujillo-Liñán (2025)	Content generation and conversational support, alongside accuracy, integrity, and over-reliance concerns.	Expands autonomy but requires ethical oversight.
Human-centered implementation	Yin et al. (2024); Mirata et al. (2020); Mustafa et al. (2024)	Adoption requires transparency, fairness, institutional readiness, and teacher involvement.	Positions AI as a partner to human expertise.

Table 3 shows that the five themes are not independent. Adaptive personalization, intelligent tutoring, analytics, and generative AI all depend on the fifth theme, human-centered implementation, for their educational value: each is accompanied in the included studies by qualifications concerning pedagogy, teacher involvement, data governance, or fairness. This pattern, rather than any single technology, is the main empirical basis for the framework developed in Section 5.

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5. The HCAI-PL Framework: Derivation and Evidence

5.1 From Themes to Dimensions

The framework was derived by mapping the themes in Table 3 and the findings in Sections 4.3 to 4.5 onto dimensions, following the procedure in Section 3.5. Table 4 shows, for each dimension, the core finding it condenses and the included studies that support it. Supporting literature outside the 26 included studies is cited only where indicated.

Table 4. Evidence base for the dimensions of the HCAI-PL framework

Dimension	Core finding condensed	Supporting included studies	Supporting literature
AI technologies	Adaptive systems, ITS, recommenders, analytics, and generative AI enable personalization but differ in aims and maturity.	Martin et al. (2020a); Troussas et al. (2021); Murad et al. (2020); Wan & Yu (2023); Xu et al. (2019); Hobert & Berens (2024); Yu & Guo (2023)	Walter (2024)
Pedagogical design	Outcomes depend on how thoroughly personalization is implemented and aligned with tasks and objectives.	Bernacki et al. (2021); Lee et al. (2021); Schmid & Petko (2019); Schmid et al. (2022); Van Schoors et al. (2021); Wang et al. (2023)	—
Learner agency	Self-regulation, metacognition, and learner control condition personalization effects.	Bernacki et al. (2021); Ackermans et al. (2025); Alé-Ruiz et al. (2024); Shemshack & Spector (2020)	—
Teacher expertise	Teachers interpret, supplement, and mediate AI; educator competence is a recurrent condition.	Hobert & Berens (2024); Lee et al. (2021); Castro et al. (2024); Ackermans et al. (2025)	Lepri et al. (2021); Barjesteh et al. (2026)
Ethical governance	Privacy, fairness, transparency, integrity, AI literacy, and institutional readiness condition trust and equity.	Yin et al. (2024); García-López & Trujillo-Liñán (2025); Mustafa et al. (2024); Mirata et al. (2020); Castro et al. (2024)	Lepri et al. (2021); Walter (2024)

Table 4 should be read as an audit trail rather than as proof. The supporting studies differ in design and strength, and several address technology-supported personalization in general rather than AI specifically. Dimensions are therefore presented as well-supported conceptual categories whose relative weight and interactions remain to be tested. Where a dimension is supported mainly by reviews, as with ethical governance, the evidence indicates that the issue is widely recognized, not that specific governance mechanisms have been shown to improve learning.

5.2 The Framework and Its Propositions

Figure 3 presents the framework. AI-supported personalized learning is placed at the center and is shaped by four interacting dimensions, all of which operate within an outer layer of ethical governance. The dimensions are not sequential; the dashed links in the figure indicate that a change in one (for instance, the adoption of a generative AI tool) calls for review of the others (for instance, task design, teacher preparation, learner support, and data policy).

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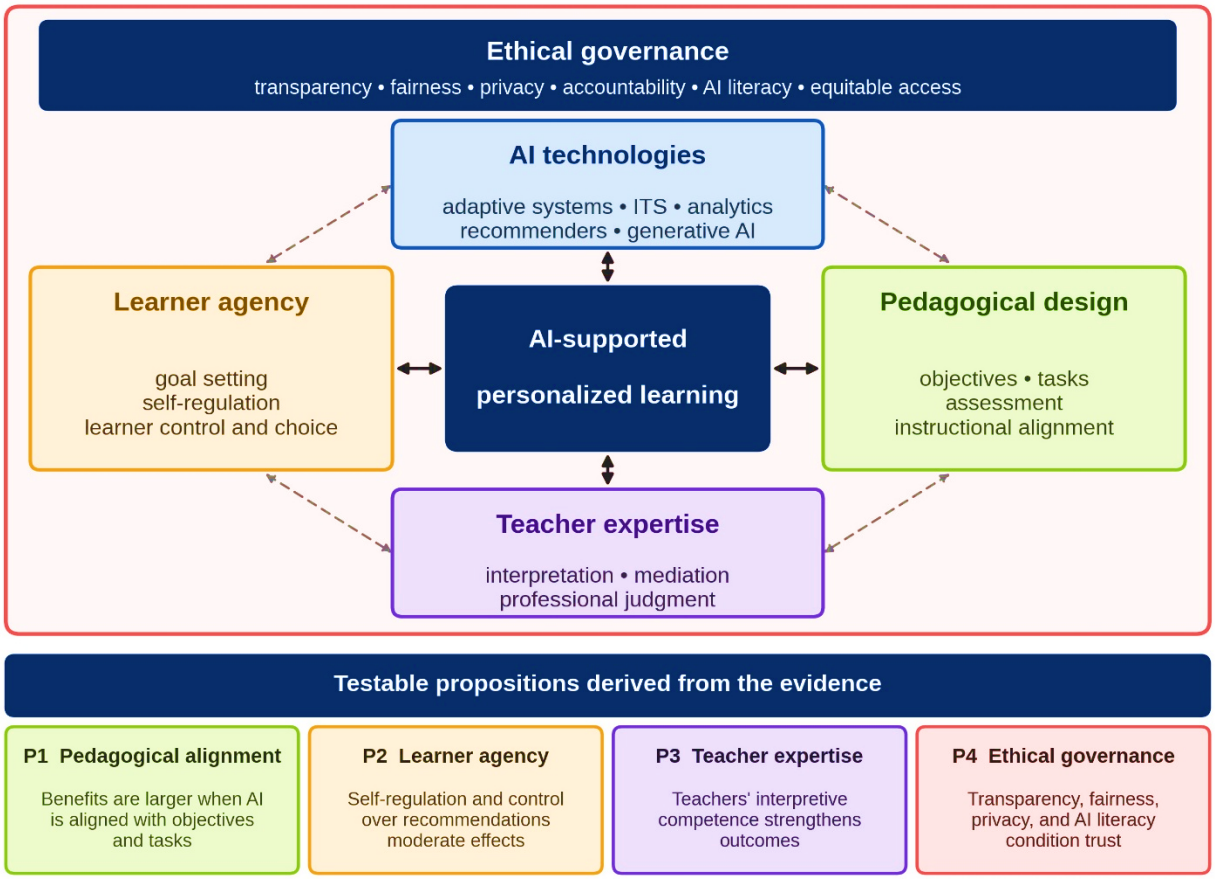


Figure 3. The integrated human-centered ai personalized learning (HCAI-PL) framework

AI technologies are the enabling mechanisms of the framework. They include adaptive systems, intelligent tutoring, recommender systems, learning analytics and predictive models, and generative AI, which differ in function and maturity (Martin et al., 2020a; Murad et al., 2020; Troussas et al., 2021; Yu & Guo, 2023). The framework treats them as means whose educational value is realized only through the other dimensions.

Pedagogical design concerns the alignment of AI functions with learning objectives, tasks, assessment, and the pace and sequence of instruction. Studies of schools and of adaptive learning suggest that outcomes vary with how thoroughly personalization is implemented and with the instructional context (Bernacki et al., 2021; Lee et al., 2021; Wang et al., 2023).

Learner agency refers to learners' capacity to set goals, monitor progress, and accept, question, or reject recommendations. Evidence on metacognition and self-regulation indicates that personalization does not automatically build these capacities (Ackermans et al., 2025; Bernacki et al., 2021), so the framework treats them as design targets rather than as by-products.

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Teacher expertise covers interpreting AI outputs, supplementing them with socio-emotional and pedagogical support, and deciding when to override them. The reviewed studies describe teachers and teaching assistants as essential intermediaries and identify educator competencies as a recurring condition for successful adoption (Castro et al., 2024; Hobert & Berens, 2024; Lee et al., 2021). Professional development for the age of AI is likewise increasingly framed in terms of teacher agency rather than skill acquisition alone (Barjesteh et al., 2026).

Ethical governance encloses the other four dimensions. It includes data protection, fairness and bias monitoring, transparency and explainability, academic integrity policy, AI literacy, and equitable access, and it operates at the level of institutions and policy (Castro et al., 2024; García-López & Trujillo-Liñán, 2025; Mirata et al., 2020; Yin et al., 2024).

The evidence supports four propositions that can be tested empirically. *P1 (pedagogical alignment):* the learning benefits of AI personalization are larger when AI functions are aligned with explicit learning objectives and task design (Bernacki et al., 2021; Lee et al., 2021; Wang et al., 2023). *P2 (learner agency):* learners' self-regulation, and their control over and understanding of recommendations, moderate the effects of personalization (Ackermans et al., 2025; Bernacki et al., 2021). *P3 (teacher expertise):* teachers' competencies in interpreting and supplementing AI output strengthen outcomes and sustain adoption (Castro et al., 2024; Hobert & Berens, 2024; Lee et al., 2021). *P4 (ethical governance):* transparency, fairness, prrivacy protection, and AI literacy condition the trust, equity, and sustainability of personalization (Castro et al., 2024; García-López & Trujillo-Liñán, 2025; Yin et al., 2024).

The framework differs from earlier models in two ways. Reviews such as Bhutoria (2022), who applied a human-in-the-loop model to personalized education in three national contexts, and Mustafa et al. (2024), who analyzed AI in education reviews through a technology-based learning model, describe or categorize the field. HCAI-PL instead specifies the dimensions that jointly condition the effectiveness of personalization and treats ethics as an enclosing layer rather than one factor among others. It does not claim that the dimensions are exhaustive or that the strength of the relationships is known; those questions require empirical validation.

5.3 Using the Framework

The framework can serve as a diagnostic and planning lens. Based on the dimensions above, the following questions are offered as a practical guide; they are derived from the framework and have not been empirically validated. For AI technologies: what decisions does the system make, and can they be explained? For pedagogical design: how do personalized activities align with learning objectives and assessment? For learner agency: can learners see, adjust, and challenge the personalization applied to them? For teacher expertise: do teachers have the preparation and the information needed to interpret and override recommendations? For ethical governance: who is

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accountable for data use, bias monitoring, and equitable access, and how are these reviewed over time? Because the dimensions interact, answers to these questions should be revisited whenever a new AI capability is introduced.

For researchers, the propositions P1 to P4 suggest concrete designs, such as comparing the same AI system under different levels of teacher mediation (P3), or varying learners' control over recommendations while measuring self-regulation and achievement (P2). For policymakers, the governance layer suggests that evaluation of educational AI should consider not only accuracy and learning gains but also transparency, fairness, and access.

6. Discussion

This review synthesized 26 studies published between 2019 and 2026. Its findings are consistent with earlier reviews that identify adaptive learning, learning analytics, and intelligent tutoring as promising routes to personalization (Bernacki et al., 2021; Martin et al., 2020a; Shemshack & Spector, 2020) and with evidence that personalized technology-enhanced learning can yield medium-sized gains (Hooshyar et al., 2024). The evidence is also consistently conditional. Gains in primary schools were limited to some subjects (Ackermans et al., 2025), and the effectiveness of personalization varied with how thoroughly it was implemented (Lee et al., 2021) and with learners' self-regulation (Bernacki et al., 2021). Technology alone therefore does not explain educational effectiveness; pedagogical design, teacher expertise, learner participation, and institutional support are recurrent conditions.

In relation to the research questions, the evidence can be summarized as follows. For RQ1, AI is applied to adapt content and pathways, provide individualized support and feedback, and inform decisions with data, mostly in higher education and, to a lesser extent, in schools. For RQ2, adaptive learning, intelligent tutoring, recommender systems, and learning analytics dominate the earlier studies, while conversational and generative AI appear later and are thinly evidenced. For RQ3, the reported benefits concern achievement, digital skills, engagement, and teacher support, while the main challenges concern privacy, bias, teacher preparedness, institutional readiness, academic integrity, and equity. For RQ4, the evidence was integrated into the HCAI-PL Framework, whose dimensions and propositions are documented in Section 5.

The review extends earlier work in three ways. First, it documents the shift from rule-based adaptation toward conversational and generative systems and shows that the empirical base for generative AI remains thin in the included studies, a point also made by recent reviews of ethical and regulatory challenges (García-López & Trujillo-Liñán, 2025). Second, it brings human-centered and ethical considerations into the analysis of personalization itself rather than treating them as external caveats, in line with calls for transparency, fairness, and meaningful human oversight (Lepri et al., 2021; Walter, 2024; Yin et al., 2024). Third, it proposes the HCAI-PL

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Framework and reports how each dimension is evidenced, which makes the derivation open to scrutiny.

The framework also connects with the broader human-centered AI literature, in which transparency, accountability, and human control are treated as design requirements rather than afterthoughts (Lepri et al., 2021). Its contribution is to specify how these requirements relate to pedagogy, learners, and teachers in the particular case of personalization. In doing so, it moves the discussion from whether AI can personalize learning toward the conditions under which personalization is educationally and ethically defensible, and it offers a vocabulary for comparing future studies that differ in technology but share these conditions.

The national findings reviewed in Section 1.1 add a contextual implication. If AI literacy and teacher preparedness shape the benefits of AI, as the Iranian studies suggest (Tusi Nasrabadi et al., 2025; Xiao et al., 2024), then the framework's emphasis on teacher expertise, learner agency, and governance is particularly relevant in contexts where these capacities are still developing. This interpretation is an inference from a small number of studies and should be tested directly.

The composition of the evidence base also qualifies the conclusions. Earlier reviews found adaptive learning research concentrated in higher education and computer science (Martin et al., 2020a) and examined digital personalized learning separately for primary and secondary education (Van Schoors et al., 2021); the present review brings these strands together with more recent work on generative AI and ethics, but it confirms that school-level evidence remains less extensive than higher education evidence. Because roughly half of the included studies are syntheses, the strongest claims concern patterns across the literature, such as the conditional nature of benefits, rather than the effect sizes of particular systems.

For educators, the framework suggests treating AI recommendations as proposals to be interpreted rather than directives, and developing AI literacy alongside subject expertise. For institutions, it implies investing in professional development, data governance, and technical infrastructure before scaling personalization, and evaluating personalization continuously rather than assigning learners permanently to algorithmically determined pathways. For developers, it implies providing transparent, explainable, and adjustable personalization that keeps teachers and learners in control. For policymakers, equitable access and clear rules on privacy, fairness, and academic integrity are preconditions rather than add-ons.

7. Conclusion

AI-supported personalized learning has progressed from isolated adaptive functions to integrated ecosystems that combine adaptive systems, learning analytics, intelligent tutoring, recommender systems, and, more recently, generative AI. Across 26 included studies, personalization was associated with benefits for achievement, engagement, feedback, and self-regulation, but these

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benefits depended on pedagogical design, teacher expertise, learner participation, and ethical governance. The HCAI-PL Framework integrates these dimensions into a single model whose derivation is documented in Section 5 and whose propositions invite empirical testing across contexts.

The practical message is that decisions about AI-supported personalization should begin with pedagogical purpose and human roles rather than with technological capability. Teachers need preparation and information to interpret and, where necessary, override recommendations; learners need transparency and a degree of control; and institutions need governance arrangements covering data protection, fairness, academic integrity, and equitable access. Where these conditions are absent, even technically sophisticated systems are unlikely to deliver sustained educational benefit.

Several limitations should be noted. Only peer-reviewed English-language publications were included, and the field is evolving quickly, particularly for generative AI; no 2026 study met the criteria. About half of the included studies are evidence syntheses, so conclusions about the direct effects of specific systems rest partly on secondary evidence. Several included studies concern technology-supported personalization in general rather than AI specifically, which may blur the focus on AI. The thematic grouping was carried out by the author team, and no inter-coder reliability statistic is reported. Finally, the framework has not been empirically validated.

Future research should test the four propositions with longitudinal and mixed-methods designs, extend evidence to under-represented educational levels, regions, and cultural contexts, evaluate the long-term effects of generative AI, and examine explainable AI that strengthens teacher and learner confidence. Educational systems that balance technological innovation with pedagogical quality, ethical responsibility, and meaningful human participation will be best placed to build inclusive, adaptive, and sustainable learning environments.

Author Contributions

"Conceptualization, H.I. and H.B.; methodology, H.I.; software, D.V.; validation, H.B., H.I. and DV.; formal analysis, H.I.; investigation, H.I. and M.R.R.; resources, M.R.R.; data curation, H.I.; writing—original draft preparation, H.I.; writing—review and editing, M.R.R. and H.Gh.; visualization, H.B.; supervision, H.I.; All authors have read and agreed to the published version of the manuscript

All authors contributed equally to the conceptualization of the article and writing of the original and subsequent drafts.

Data Availability Statement

Data available on request from the corresponding authors.

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Conflict of interest

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