Review Article

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Mapping Personalized Learning in Medical Education: A Meta-Synthesis of Artificial Intelligence Applications

AVA TAGHAVI MONFARED[1], MSc; MARYAM HOJATI[2], PhD Candidate; ZOHREH FARAHMANDPOUR[3], PhD Candidate; AHMAD KEYKHA[4*], PhD

[1]Department of Educational Administration and Planning, Faculty of Psychology and Education, University of Tehran, Tehran, Iran; [2]Faculty of Literature and Humanities, Guilan University, Rasht, Iran; [3]Educational Leadership Teaching and Administration, Department College of Education, University of North Texas 1155 Union Circle, Denton, Texas, 76203-5017, USA; [4]Department of Educational Management, Faculty of Psychology and Education, Kharazmi University, Karaj, Iran

Abstract

Introduction: The rapid advancement of Artificial Intelligence (AI) in medical education is driving a shift from traditional instructional design methods toward personalized and adaptive learning models. Despite numerous promising applications, the available evidence remains limited and fragmented; therefore, a comprehensive synthesis of the evidence is needed to support robust conclusions.

Methods: This study employed the four-phase meta-synthesis framework proposed by Sandelowski and Barroso. A systematic search was conducted across Medline, Embase, CINAHL, PsycINFO, PubMed, Web of Science, ScienceDirect, Wiley Online Library, SpringerLink, Taylor & Francis Online, SAGE Journals, and Scopus, covering publications from 2010 to 2025. Studies were screened according to predefined inclusion and exclusion criteria, and their methodological quality was evaluated using the Critical Appraisal Skills Programme (CASP). Coding reliability was assessed through a test–retest procedure, resulting in a reliability coefficient of 0.81.

Results: A total of 273 records were identified, of which 16 studies met the inclusion criteria and obtained CASP scores exceeding the threshold of 30. Content analysis revealed five principal domains: faculty-related applications (21%), student-related applications (28%), applications in the learning process (15%), curriculum development (13%), and assessment mechanisms (23%). Student-related applications constituted the largest proportion, highlighting the pivotal role of learner-centered personalization in AI-driven medical education.

Conclusion: The integration of Artificial Intelligence (AI) into individualized educational experiences represents a transformative model for medical education. AI enables adaptive learning pathways, dynamic assessment methods, and data-driven instructional environments, thereby enhancing student engagement, fostering faculty innovation, and promoting equity in learning outcomes. This synthesis proposes an overarching conceptual framework to inform policy, research, and implementation in the context of AI-supported personalized medical education.

Keywords: Artificial intelligence, Educational technology, Medical education, Self-directed learning

**Corresponding author:*
Ahmad Keykha, PhD;
Department of Educational Management,
Faculty of Psychology and Education,
Kharazmi University,
Karaj, Iran
Tel: +98-9129583889
Email: ahmadkeykha8984@gmail.com

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Introduction

The ways in which healthcare professionals learn, both individually and collaboratively, have been transformed by technology-enhanced learning, particularly through the integration of artificial intelligence. Furthermore, AI has also changed how students are prepared for careers in healthcare, how research is conducted, and how performance is evaluated (1–7). Along with the educational challenges posed by using AI in the classroom, one challenge healthcare educators face is addressing ethical issues (e.g., data privacy, algorithm bias, and transparency). To successfully adopt AI, appropriate oversight and ethical guidelines are needed to support its ethical use by all stakeholders, minimize risks, and maximize potential benefits (8, 9). Given the rapid pace of technological change, timely action is required to ensure that future healthcare professionals receive adequate education and training to use AI effectively (10). Therefore, it is essential that medical education programs and curricula adapt to the rapidly changing environments in which they operate.

The application of artificial intelligence in medical education has evolved rapidly through large language models (LLMs), which are systems capable of understanding and generating human-like natural language (11). LLMs are used to provide realistic clinical scenarios and constructive feedback to learners while creating individualized learning environments that accommodate each learner's pace, style, and characteristics. Personalized learning emphasizes the development of learning processes that reflect individual learner characteristics, including abilities, preferences, prior knowledge, interests, and goals. It requires continuous and automated adaptation to ensure that learners' knowledge and competency levels remain up to date (12).

Personalized learning originated in classical educational psychology and focused on tailoring instruction to each learner's individual profile. Benjamin Bloom's classic 1984 study, entitled the "2 Sigma Problem," demonstrated that students who received individual, instructor-led tutoring performed, on average, two standard deviations higher than their non-tutored counterparts in traditional classroom settings. This work led to substantial subsequent research on adaptive instructional methods and the use of technology for instructional delivery. Barbara Means and other researchers have contributed to the body of research on personalized learning in medical education. Means demonstrated that blended learning and student-centered approaches were effective in digital learning environments (13). As additional empirical studies have been published, the positive impact of personalized learning on academic achievement, metacognitive awareness, and motivation has continued to be demonstrated (14, 15). Taken together, this evidence points to the need to redesign medical education with the support of emerging AI capabilities.

Although active learning methods have been gradually adopted in medical education, educational systems still predominantly rely on a one-size-fits-all model. This can be problematic because medical students enter educational programs with varying levels of academic preparedness, learning styles, and prior knowledge. Because educational value added is closely related to learners' background knowledge, these differences can result in learning gaps for some students and suboptimal experiences for others. This not only negatively affects the quality of the educational experience but also is in conflict with core principles of educational equity (16). Advances in AI, particularly those enabled by LLM-based technologies, present new opportunities for student-centered instructional adjustment and enhanced personalization. The purpose of this study is to identify the application of advanced learning technologies in creating personalized learning opportunities for medical students.

Research Contribution

Previous investigations examining the use of artificial intelligence to support individualized learning approaches among medical students have largely been conducted as independent and uncoordinated studies employing limited methodologies. Consequently, there is no single source that provides a comprehensive synthesis of the potential of AI-based personalization within medical education. Accordingly, the present study employs a meta-synthesis methodology to conduct a comprehensive and interpretive qualitative analysis of the existing literature on this topic. Following a systematic screening process and an exhaustive content analysis of the identified studies, this investigation delivers a multidimensional, contextually relevant, and action-oriented framework for the development and application of AI technologies to support effective personalized learning in medical education. By integrating disparate findings across the literature, this study contributes to a deeper understanding of the key concepts, emergent patterns, and practical recommendations for the design and implementation of adaptive medical education. As such, the findings provide a meaningful contribution to the interdisciplinary discourse at the intersection of medical education and educational technology.

Table 1: Inclusion and exclusion criteria

Inclusion Criteria	Exclusion Criteria
- Must involve applications of artificial intelligence in personalizing learning for medical students - Must involve a research framework - Must be written in the English language - Must be published between 2010 and 2025	- Articles on personalizing learning, but not in the medical field - Articles without a research framework - Articles published in languages other than English - Articles outside the time range

Table 2: Search strategy for the meta-synthesis

Boolean operator	Keywords / MeSH terms	Concept
OR	"Education, Medical"[MeSH]; "Medical Education"; "Health Professions Education"; "Clinical Education"; "Undergraduate Medical Training"; "Graduate Medical Education"	Medical Education
OR	"Personalized Learning"; "Individualized Learning"; "Adaptive Learning"; "Tailored Education"; "Customized Learning"; "Self-directed Learning"	Personalized Learning
OR	"Artificial Intelligence"[MeSH]; "Artificial Intelligence"; "AI"; "Machine Learning"; "Deep Learning"; "Neural Networks"; "Natural Language Processing"; "Educational Data Mining"; "Intelligent Tutoring Systems"	Artificial Intelligence
OR	"Systematic Review"[Publication Type]; "Meta-synthesis"; "Qualitative Review"; "Evidence Synthesis"	Review filter
AND	2010/01/01 – 2025/12/31	Date limit

Methods

This study was conducted in accordance with the four-phase framework proposed by Sandelowski and Barroso (17, 18), encompassing a rigorous search strategy, critical appraisal of eligible studies, classification of the evidence, and synthesis of key findings. The combined use of systematic review and meta-synthesis provided a structured methodological approach to examine and formally integrate the findings of prior research (19), thereby generating cohesive insights grounded in accumulated empirical evidence.

Selection criteria

Articles that met the inclusion and exclusion criteria listed in Table 1 were analyzed for the meta-synthesis research.

Following the criteria for meta-synthesis outlined above, this study excluded non-primary research articles, conference abstracts, letters to the editor, books, and unpublished reports, as these sources do not meet the standards for rigorous integration. The search was further limited to English-language publications between 2010 and 2025, which may have resulted in the omission of relevant non-English studies. The exclusion of non-research and unpublished materials may also have omitted important perspectives typically included in grey literature.

Data Sources and Searches

An information specialist conducted a systematic literature review using multiple bibliographic databases. Databases searched included Medline, Embase, CINAHL, PsycINFO, PubMed, Web of Science, ScienceDirect, Wiley, SpringerLink, Taylor & Francis, and SAGE. The literature search included peer-reviewed articles published between January 1, 2010 and June 20, 2025, that provided evidence of the use of artificial intelligence in personalized learning. The bibliographic records were entered into an Excel spreadsheet and organized in a structured database to facilitate systematic screening and citation tracking. In this manner, the four members of the research team conducted an independent two-phase screening process (M-H, A-T, A-K, Z-F). The screening process consisted of an initial title and abstract review based on the predefined inclusion criteria of the study, followed by a full-text review for final inclusion. To enhance the quality of the review process, individuals outside of the original reviewer pool independently assessed each article during the quality appraisal stage. This approach provided an additional layer of verification and facilitated the resolution of differences in opinion regarding the article quality. Three major concept areas were used to develop a comprehensive systematic search strategy: medical education, learner-centered education, and artificial intelligence technology. Each concept area included multiple terms with similar meanings; therefore, terms within each area were combined using OR, while the three concept areas were combined using AND. To increase the precision of the search results, we applied limits to include only systematic review articles published between 2010 and 2025. The complete systematic search strategy, including medical subject headings and free-text terms, is presented in Table 2.

Further backward reference searching of the selected full texts was conducted to capture studies that may have been missed in the initial query.

Any disagreements or discrepancies in the study selection were resolved through deliberation with a panel of three external reviewers, ensuring consensus and methodological transparency (Table 3). Figure 1 presents the PRISMA form in the article screening process.

Quality Appraisal

To evaluate the methodological quality of the included studies, we applied the Critical Appraisal Skills Programme (CASP). CASP provides a structured framework consisting of ten core questions designed to assess the credibility, relevance, and rigor of research. Building on the approach developed by Long, et al. (36) and previously employed in meta-synthesis studies (37), the CASP tool was operationalized into a 10-item checklist to enable a more granular and systematic appraisal. Two reviewers (A-K and M-H) independently conducted quality assessments using this expanded tool, with any discrepancies resolved through consultation with a third reviewer (A-T or Z-F). The ten CASP criteria included clarity of research aims; appropriateness of methodology; suitability of research design; adequacy of recruitment strategy; rigor of data collection; consideration of researcher–participant relationships; attention to ethical issues; rigor of data analysis; clarity of the findings; and overall value of the research. Each criterion was scored on a 0–4 scale (0 = not addressed; 4 = fully addressed), yielding a maximum possible score of 40 points. A cut-off score of 30 points (≥75%) was established as the minimum threshold for methodological adequacy; studies scoring below this threshold were excluded. As a result, all 16 included studies achieved scores above the threshold and were positively appraised (38).

Analysis and Synthesis

Data were interpreted using an inductively oriented text analytic approach (39). Following the extraction and transcription of relevant sections from each identified article, multiple read-throughs were conducted to ensure a general understanding of the primary messages of the articles. The entire article served as the unit of analysis; therefore, the data were deconstructed into condensed meaning units ranging from single words to complete sentences or paragraphs that represented thematically related concepts.

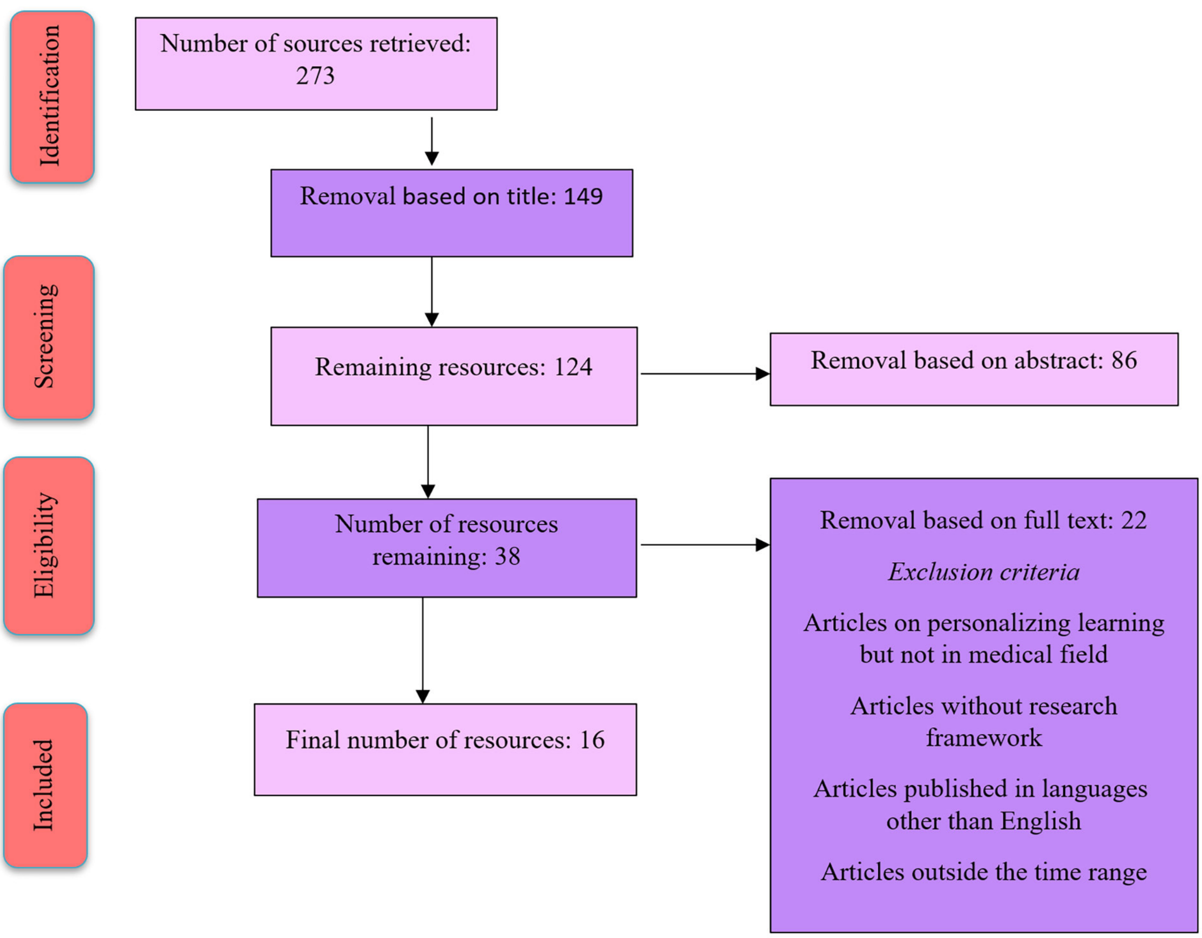

Figure 1: The PRISMA form in the article screening process

Table 3: Bibliographic characteristics of the selected articles

Reference number	Authors	Year	Purpose	Method	Key findings	CASP
(20)	Hanif,& Mustafa	2023	To explore how AI, machine learning, and cloud computing are transforming personalized learning and precision medicine.	Conceptual review and synthesis of current trends and applications in education and healthcare.	AI and ML personalize education through adaptive learning and predictive analytics, improving engagement and outcomes. Cloud computing enhances access and scalability. In healthcare, AI enables precision medicine via early disease detection, customized treatment, and accelerated drug discovery. Ethical challenges like data privacy and bias remain significant.	50
(21)	Obeagu, et al.	2024	To examine the role and benefits of Personalized Learning Plans (PLPs) in addressing the educational needs of students with Sickle Cell Disease (SCD).	Narrative literature review and expert synthesis based on educational and clinical practice perspectives.	PLPs provide tailored educational support for students with SCD, improving academic success, social inclusion, and well-being. They address both academic and psychosocial needs through accommodations, collaboration among stakeholders, and empowerment of students. Recommendations include teacher training, collaborative development, and individualized services.	42
(22)	Bahmani, et al.	2023	To evaluate the effectiveness of personalized learning in enhancing cognitive efficiency and learning outcomes in clinical education using scenario-based approaches.	Experimental and observational case study in clinical settings with data from digital platforms and learner feedback.	Personalized learning improves clinical decision-making, cognitive efficiency, and real-time knowledge transfer. Scenario-based modules and real-time feedback contribute to faster learning and reduced faculty workload. Integration of adaptive systems is key to personalized clinical education.	46
(23)	Yovanoff, et al.	2023	To investigate how real-time, multisensory feedback in virtual environments enhances personalized learning in health professional education.	Mixed-methods study involving VR simulation, structured observation, and thematic analysis of learner experiences.	Real-time personalized feedback in virtual simulations improves skill acquisition, engagement, and situational learning. Graphical and multisensory feedback supports learners' self-regulation and clinical readiness. Personalized virtual environments offer scalable strategies for adaptive education.	45
(24)	Ali, et al.	2024	To outline a scoping review protocol for mapping current literature on personalised learning in health sciences higher education, including definitions, implementation strategies, benefits, and limitations.	Scoping review protocol based on Arksey & O'Malley framework and PRISMA-ScR guidelines; planned database searches and thematic synthesis of studies from 2000 to 2023.	This protocol anticipates identifying heterogeneous definitions and models of personalised learning and aims to synthesize implementation strategies, benefits, limitations, and research gaps in the field. It stresses the potential of personalised learning to enhance engagement and reduce attrition in health sciences education, while also acknowledging challenges like digital inequity and data privacy.	41
(25)	Raeisi, et al.	2019	To evaluate the effectiveness of a modified Student Personalized Learning (SPL) protocol in enhancing metacognitive skills and academic performance among health science students.	Cross-sectional study with 22 undergraduate students using pre/post assessments, advisory sessions, and structured SPL modules over 16 sessions.	The SPL approach improved metacognitive skills from average to very good levels, particularly in self-regulation, planning, and control of oneself. Academic performance increased significantly (mean final score 16.72 vs. pretest 10.7). However, control of process evaluation remained unchanged, indicating a limitation of short-term SPL in enhancing self-evaluation.	43

Reference number	Authors	Year	Purpose	Method	Key findings	CASP
(26)	Rojanasarot, et al.	2018	To assess whether personalized learning objectives in an online health care course influenced student engagement and whether achievement could be measured through course assignments.	Mixed-methods study involving content analysis of student reflections, course evaluations, and assignment performance over four semesters.	Personalized learning objectives enhanced student engagement and could be measured through course deliverables. Students reported increased connection between content and personal goals, better communication skills, health literacy, and professional motivation. Most students confirmed achievement of their objectives; suggestions included allowing revisions during the course.	46
(27)	Stambuk-Castellano, et al.	2024	To investigate the impact of personalized learning based on metacognitive profiles and question difficulty levels on medical students' performance in respiratory and digestive system units.	Experimental intervention study involving 91 first-year medical students; use of Moodle to deliver personalized and traditional learning paths in control and experimental groups.	In the digestive unit, students receiving personalized learning significantly outperformed those in the traditional group ($p<0.001$). In the respiratory unit, no significant difference was observed. Aligning question difficulty and content with students' metacognitive profiles improved motivation, autonomy, and conceptual understanding. Students rated the personalized experience as more useful and satisfying.	47
(28)	Kelly, et al.	2014	To explore whether the success of community-based medical education (CBME) is attributable to meaningful personal learning experiences in longitudinal integrated clerkships.	Theoretical and narrative analysis drawing from educational theory and CBME program evaluations; synthesis of experiential and situated learning concepts.	CBME fosters rich relationships with preceptors, patients, and the community, promoting continuity, trust, and meaningfulness in clinical learning. Meaningful experiences in small, socially-integrated communities enhance clinical reasoning, communication skills, and professional development. The model highlights how authenticity, socialization, and community engagement strengthen personalized and context-rich learning.	43
(29)	Abedi, et al.	2021	To investigate the impact of personalized learning on achieving significant learning outcomes based on Fink's taxonomy in higher education.	Experimental pretest-posttest control group design with 30 undergraduate students in a media education course. Personalized learning paths were based on cognitive styles and included choice of authentic assignments. Comparison made with a control group receiving traditional online instruction.	Students in the personalized group showed significantly higher gains in content mastery, cognitive, agentic, and emotional engagement, and self-regulated learning ($p<0.05$). Personalized learning enhanced integration, caring, human dimension, and learning to learn dimensions. The study recommends implementing personalized environments to achieve meaningful learning in higher education.	68

Reference number	Authors	Year	Purpose	Method	Key findings	CASP
(30)	Sadeqi-Arani, et al.	2025	To explore the potential benefits and applications of the Internet of Behaviors (IoB) in educational businesses, particularly in fostering personalized, sustainable, and smart learning.	Conceptual and narrative commentary based on a synthesis of literature and real-world examples across behavioral analytics and educational technology.	IoB supports personalized learning by analyzing behavioral data to tailor instruction, provide real-time feedback, enhance collaboration, and enable early intervention. It contributes to health and safety via wearable tech, fosters smart classrooms, improves resource allocation, and facilitates continuous professional development. Challenges include data privacy, access equity, and technical complexity. The paper emphasizes the need for ethical frameworks and future research to integrate IoB with pedagogy.	44
(31)	Rabie	2023	To propose a conceptual framework for Intelligent Personalized Education (IPE) in clinical education using AI, data analytics, and real-time feedback mechanisms.	Theoretical model development based on literature review, integrating educational theories with data-driven and adaptive learning systems.	The IPE framework outlines six core components: personalized learning, intelligent feedback, clinical decision-making support, learning analytics, adaptive content delivery, and self-regulated learning. AI enables dynamic adaptation of content and assessments based on learner profiles. The model emphasizes precision in competency development and real-time educational guidance, offering a roadmap for AI integration in clinical training.	47
(32)	Sunmboye, et al.	2025	To propose a model of Smart Self-Regulated Personalized Learning (SSRPL) integrating AI-based adaptive feedback and cognitive load theory to optimize personalized instruction.	Conceptual paper presenting a theoretical framework integrating literature on SRL, AI, and cognitive load management in personalized learning environments.	SSRPL leverages real-time AI feedback and intelligent monitoring to help learners adjust goals, strategies, and pace. The model aligns with cognitive load theory to prevent overload and promote efficient knowledge acquisition. Applications include workload balancing, adaptive scaffolding, and enhancement of learner autonomy through metacognitive support.	55
(33)	Shen, et al.	2025	To explore nursing students' perceptions and experiences of using Generative AI (GenAI) in clinical case learning in China.	Qualitative study using semi-structured interviews with 17 third-year nursing students after engaging with GenAI tools in a clinical case learning context; data were analyzed thematically.	Students reported GenAI enhanced efficiency in structuring case reports and generating care plans, but required critical revision and lacked emotional nuance. Prompt quality significantly influenced output relevance. Concerns included over-reliance, ethical use, and patient data privacy. GenAI was perceived as a useful supplement but not a replacement for human empathy and professional judgment.	47
(34)	Hu, et al.	2025	To explore nursing students' perceptions and experiences of using Generative AI (GenAI) in clinical case learning in China.	Qualitative study using semi-structured interviews with 17 third-year nursing students after engaging with GenAI tools in a clinical case learning context; data were analyzed thematically.	Students reported GenAI enhanced efficiency in structuring case reports and generating care plans, but required critical revision and lacked emotional nuance. Prompt quality significantly influenced output relevance. Concerns included over-reliance, ethical use, and patient data privacy. GenAI was perceived as a useful supplement but not a replacement for human empathy and professional judgment.	49

Reference number	Authors	Year	Purpose	Method	Key findings	CASP
(35)	Yovanoff, et al.	2017	To develop and evaluate a personalized learning interface within a Dynamic Haptic Robotic Trainer (DHRT) for training surgical residents in ultrasound-guided central venous catheterization (CVC).	Two-phase study: Phase 1 involved content analysis of expert feedback to 18 third-year medical students to identify key learning elements; Phase 2 involved the design and usability testing of a personalized feedback interface with 8 surgical residents using simulated CVC scenarios.	Feedback on critical elements like needle angle, aspiration technique, and vessel identification was incorporated into a personalized interface. Participants rated personalized feedback, especially visual feedback and grading components, as highly useful. Improvements included graphical tips, real-time metrics, and video tutorials. The DHRT system shows promise for competency-based, individualized skill development in surgical training.	44

Condensed meaning units were then consistently interpreted and assigned descriptive codes. Subsequently, codes with similar conceptual themes were compared and clustered to create preliminary sub-themes through thematic aggregation. This iterative process of coding and theme review continued until theme saturation was achieved, defined as the point at which no additional codes, categories, or insights emerged from the data. Theme saturation supported the validity and completeness of the analytical framework by confirming that the final set of themes represented the full scope of evidence across the included studies.

Data Validation

The reliability of the coding process was evaluated using an internal consistency test applied to all conceptual elements generated during analysis. A validation strategy was implemented through a repeated categorization process conducted independently by a single researcher at two separate time points. By comparing the results from both coding rounds, the consistency of code assignment was assessed. The codes that matched across both rounds were classified as “matched,” whereas those that did not were classified as “unmatched.” A ratio of matched to unmatched codes was subsequently calculated and used to determine test–retest reliability. In this study, the interval between coding rounds was 20 days, and both rounds were conducted by the same researcher. A total of 331 distinct codes were generated, of which 135 were assigned consistently across both coding rounds. Based on these results, a reliability coefficient of 81% was calculated, exceeding the accepted standard of 60% for test–retest reliability (40). Accordingly, the coding framework demonstrated stability and credibility, further supported by peer review and evaluation by external experts not affiliated with the research team (41–44).

$$\text{Test-Retest Reliability} = 100 \times \left(\frac{135\times2}{331}\right) = 81\%$$

Results

Through the meta-synthesis, we identified five main categories (and related sub-categories): (i) applications for faculty members; (ii) applications for students; (iii) applications in the learning process; (iv) curriculum development; and (v) development of student assessment mechanisms. Table 4 presents a detailed description of all main themes and subthemes.

The dataset created from the previously described classifications of extracted data was assembled into five overarching themes, yielding sixteen sub-themes and 192 key concepts that define multiple components of personalized learning in medical education.

The first overarching theme, *“Applications for Faculty Members,”* consists of five sub-themes with 41 key concepts. These concepts address topics such as aligning instructional delivery with varied learning styles, utilizing data to design instruction, and supporting faculty in managing instructional processes to enhance teaching effectiveness.

The second theme, *“Applications for Students,”* includes four sub-themes and the largest number of key concepts in this analysis, totaling 53. These concepts cover diverse aspects of student development, including individual learning trajectories, cognitive and non-cognitive skill development, self-regulation, and support for informed academic and career decision-making.

The third theme, *“Applications in the Learning Process,”* comprises two sub-themes with 28 key concepts. This theme highlights the

Table 4: Results of content analysis of articles

Main themes	Sub-themes	Key concepts (Sample References)
Applications for Faculty Members	Personalized Education	Identification of diverse learning styles (30); development of personalized teaching approaches (20); adaptive instructional frameworks for individual differences (21); data-driven instructional models (24); personalized interventions (24); individualized performance strategies (25); student-centered instructional design (25); refined teaching for personalization (27); task delegation based on student progress (28); reflective teaching and individualized classroom management (30); alignment of content with assessments and learner preferences (31); adaptation to cognitive profiles (33); scalable personalized education models (20); learner-centered strategies and data analytics for need identification (20, 21); targeted support plans and group interaction design based on individual differences (21, 29); alignment of goals, knowledge, and strategies with learner characteristics (27); capability-based teaching customization (21); individualized instructional guidelines (24); equitable, targeted support (21); real-time resource allocation (20); innovative teaching through personalization (27); instruction responsive to varied learning styles and individual learner goals (30, 31).
	Development of Instructional Design Approaches	Personalized learning objectives based on individual needs (31); course difficulty adaptation from prior interactions (34); real-life aligned project and assignment design (29); context-instructional design development (20); multidimensional learner support programs (21); instructional planning incorporating individual and cultural needs (25); learner-centered educational programs (25); development supportive strategies for effective learning environments (25); development structured student teams for collaboration (29); clinically authentic role-based scenarios (28); alignment of projects and resources with professional goals (30); personalized study plans and assessments (32); scenario-based clinical practice support (33); development adaptive and data-informed instructional strategies (21); development creative learning experiences and supportive educational platforms (25)
	Development of Educational Models	Evidence-based clinical education emphasis (28); integration of learning analytics for tracking progress and faculty insights (31, 34); analysis of student perceptual patterns (20); fostering awareness of clinical student growth (28); practical and responsive instruction (25); adaptive learning in clinical contexts (31); faculty development in interactive teaching (20); strategies for student engagement, learning pattern recognition, academic history analysis (20); instructional timing based on content volume and learner needs (32); theory-to-practice transfer in clinical education (33); frameworks for diverse educational needs (21); flexible learning goal-setting (29); competency-based education with cognitive alignment strategies (27); responsive and supportive instruction (30).
	Development of Communicative Actions	Monitoring of student communication and group participation (30); use of participation data for networked learning (30); instructional adjustment based on prior interactions (34); data-informed pedagogy emphasis; development of collaborative educational approaches (21); creation of supportive and inclusive learning environments (21); faculty-student engagement through authentic learning contexts (28); improved teamwork quality via learning analytics (30).
	Management of Faculty Members' Activities	Cognitive load awareness and instructional management (32); educational data analysis and insight extraction (24); reduced faculty workload (20); targeted interventions and transformed faculty support (20); time-saving mechanisms for instructors (33); comprehensive learner profiles for decision-making (30).
Applications for Students	Personalized Learning	Personalized learning pathways shaped by prior experiences (29, 22, 35); documentation of progress and goal attainment (29); content selection based on individual needs (22, 29); profiling learning processes (27); leveraging cognitive preferences to increase engagement and reduce misunderstandings (27, 29); addressing conceptual difficulties (30); adaptive study plans and individualized trajectories (32); integration of past experiences with new goal-setting (29); consideration of perceptions, backgrounds, and prior knowledge (31); student awareness of learning challenges (34); aligning experiences with personal needs (23, 35); personalized and diversified assignments (21); adaptation to strengths and weaknesses (21); overcoming learning barriers (21); promotion of self-regulation and learner agency (24); linking academic trajectories to personal goals (29); readiness-informed instructional design (27); responsiveness to comprehension, interest, and background (30); ongoing goal revision and experience-based redefinition (29); addressing individual differences and applying analytics for growth (21, 24); data-driven personalization and trajectory mapping (24, 29); interest development through meaningful engagement (29); goal-, competency-, and preference-based pathway design (27, 29); multiple routes to shared objectives (29); emphasis on individual choice and psychological preferences (29); performance-informed and difference-responsive design (24, 31); leveraging learner capacity, pace adjustment, dynamic responsiveness (25, 29); enriching instruction through diverse perspectives and autonomy support (29, 31).

	Development of Cognitive and Non-Cognitive Skills	Personalized and reflective strategies for real-life problem-solving (29, 35), continuous professional development (30), clinical decision-making (33); enhancement of technical/practical skills (34), metacognitive abilities (24), critical thinking and problem-solving (24); self-regulation and autonomy (25), self-awareness, agency, confidence (21, 24); sense of ownership, academic belonging, learning value (21); positive attitudes toward learning (21); classroom participation and collaboration (24, 32); openness to feedback, perspective development, higher-order thinking (29); summarization of complex concepts, teamwork, lifelong learning (29, 30); decision-making skills (33); improved self-awareness and attitudes (25); professional role internalization, personal efficacy shifts (29); transformed thinking processes and insights (29); emotional and professional growth through clinical engagement (28); enhanced clinical performance (28), learning capacity (23), reduced academic stress (21); increased motivation and learning satisfaction (24); inclusion and empowerment of learners with special needs (24); academic motivation and engagement (25); authentic team roles in clinical contexts (28); learning enjoyment, satisfaction, motivation (29); academic performance via personalized instruction (32); time efficiency through goal-driven learning (33); positive educational experiences and intrinsic motivation (29); integrated feedback, critical thinking, decision-making in complex scenarios (33); improved interpersonal, communication, and clinical competencies (28).
	Improvement of Students' Personalized Learning Processes	Technology-enhanced, personalized learning environments (23); unlimited access to knowledge repositories (20); clinical information organization (33); reinforcement exercises and alternative explanations (34, 20); support for non-traditional and disabled learners (24); alignment of content with individual goals (29); simplified understanding of technical content (29); adaptation to diverse learning approaches (27); peer discussion for conceptual clarity (29); data-driven insights for improved outcomes (30); goal-directed guidance to reduce overload and fatigue (32, 21); flexible instructional strategies (27); time and resource management (32); bridging theory and clinical practice with practical scenarios (33); knowledge transfer in complex healthcare situations (33); targeted instructional support (34); real-time discussion participation (20); self-assessment and learning effectiveness monitoring (25); cognitive and temporal efficiency (33).
	Optimization of Academic and Career Decision-Making	Enhanced self-awareness and career pathway clarity (29); lived experiences as drivers of academic/professional decisions (28); real-life contextual learning for deeper comprehension (29); data-driven academic advising (27); personalized environments for informed educational and career choices (29); pathway decision analysis (29); evaluation of internship progress and success link (28); contextualized learning and career decisions (28); academic trajectory shaped by personal feedback (29); empirically informed, professionally aligned programs (30); supportive and engaging learning journeys (34); personalized career counseling (34); alignment of studies with individual goals (29); improved internship outcomes and meaningful career development (28).
Applications in the Learning Process	Fostering Excellence in the Learning Process	Evidence-based strategies and observational clinical learning (29, 28); interest-driven engagement (29); visual and customized formats (30); multisensory and sustainable learning (23); flexible, personalized, structured processes (20, 21); learning analytics for instructional insight (24); learning styles/preferences analysis for alignment (24); inquiry-based learning and cognitive load reduction (25, 31); theory-application integration in clinical scenarios (33); strengthened transfer skills (33); constructivist, interactive, and situated learning (33, 23); digital platforms and simulations for remote learning (20); adaptive learning platforms and personalized tech integration (24); monitoring and regulation of learning behaviors (25); knowledge transfer through student-centered approaches (25); engaging, emotionally resonant learning (26); small-group experiential/affective structures (28); intentional structuring of clinical activities for professional development (28).
	Development of the Teaching–Learning Environment	Online learning tailored to individual pathways (26); dynamic and adaptable learning packages (31); alignment with metacognitive preferences and learning styles (27); respect for cognitive, emotional, and experiential diversity (29); personalized environments for diverse learners and equitable access (24, 26); learning as interaction within clinical contexts (28); student-faculty real-time collaboration in shared spaces (20); responsive digital systems for continuous learning analysis (34); flexible and learner-responsive environments (21); data- and performance-based platforms for personalized ecosystems (32); adaptive digital environments supporting sustained engagement (34); virtual reality integration with situated content for contextualized, deep learning (23).

Curriculum Development	Curriculum Personalized	Adaptive curriculum design aligned with learner preferences (30); personalized curriculum plans (20); content tailored to student needs (20); instructional content adjusted to progress (24); individualized progress analytics for content sequencing (29); learner needs, capacities, and goals in content development (31); adaptation to cognitive load and performance level (32); customization of curriculum content and processes (24); co-designed curricular frameworks reflecting student input and needs (30).
	Curriculum Dynamization	Digital resource integration for curriculum personalization (20); narrative-based content for engagement (29); immersive learning experiences (20); cultural background in instructional delivery (25); curriculum analytics for content gap identification (30); content alignment strategies for medical comprehension (31); reusable modular components (21); enhancement of traditionally less engaging content (26); real-time data for personalized content delivery (32); data-informed curriculum design (20); flexible structures aligned with evolving capabilities (27); non-linear, diversified content to prevent monotony and support differentiation (29).
Development of Student Assessment Mechanisms	Personalization of Assessment	Personalized assessment practices (24); real-time individualized feedback and recommendations (31, 32); feedback-informed strategy adjustment (34); competency-based analytics for adaptive test design (27); performance-based guidance for learning paths (31); personalized assessments and complexity-matched questions (27); authentic assignments aligned with preferences (30); graphical feedback in clinical contexts (23); equitable and targeted support (21); personalized evaluations emphasizing individual performance (24); goal-fulfillment documentation and contribution-based feedback (26); pathway-aligned assessments (27); evaluation of goal achievement across experiences (29); alignment of instructional styles with preferences/capacities (31); assessment of cognitive, problem-solving, decision-making skills (33); quality monitoring of feedback via learner responses (23).
	Data-Driven Assessment	Empirical and cognitive-preference-based trajectory evaluation (27); data-informed refinement of instructional content (30); analytics-based educational decision-making (34); real-time contextual feedback from professional tasks (28); behavioral data tracking and analysis (30); adaptive assessment adjustment (32); early identification of at-risk students (20); purposeful formative assessment design (30); student data management in adaptive evaluation (31).
	Enhancing the Efficiency of Assessment Systems	Feedback aligned with real-world clinical contexts (23); interactive, multimodal feedback for engagement (23); immediate textual, graphical, real-time support (34, 23); virtual reality in feedback delivery (23); data-driven performance and behavior analysis (20); automated grading systems (20); evaluation of learning strategies and outcomes (25); feedback impact on professional performance (28); alignment of feedback with situational context (23); multimodal feedback enhancing conceptual understanding (23); continuous evaluation of learning path quality (28); structured self-assessment for metacognitive growth (25); monitoring strategies for efficacy (25); formative assessment models (27); feedback-mediated learning level adjustment (27); clinical progress evaluation in faculty-student interactions (28); observer reinforcement for field performance (28); assessment of professional team participation quality (28); peer feedback for reflection and engagement (29); individual and group evaluation of collaborative learning (30); adaptive instruction effectiveness in complex understanding (31); stepwise feedback mechanisms for performance (32); efficiency evaluation in high-stakes clinical scenarios (33); personalization reducing human error in evaluation (34).

transformative role of adaptive technologies, the use of realistic clinical case scenarios, and the creation of multisensory and responsive learning environments as essential elements in reshaping the learning process.

The fourth theme, *"Curriculum Development,"* includes two sub-themes and 25 key concepts. It emphasizes flexible content, modular and non-linear curriculum structures, and the involvement of learners as co-designers of the curriculum, promoting ownership and deeper engagement with the educational material.

The fifth theme, *"Development of Student Assessment Mechanisms,"* consists of three sub-themes and 45 key concepts. These focus on data-driven analytics, adaptive assessment strategies, context-aware assessment, and dynamic feedback mechanisms to improve the accuracy, efficiency, and equity of student evaluation.

Overall, this analytical framework demonstrates that individualized learning impacts all aspects of the educational system—from curriculum to pedagogy, assessment, and learner experience—creating innovative ways to advance medical education. These results are presented in Figure 2.

The relative distribution of the main themes identified in this review is shown in Figure 2. The largest proportion (28%) is associated with *Applications for Students*, reflecting the importance of a student-centered approach to personalized learning, as demonstrated by adaptive learning pathways, cognitive-emotional development, and goal-driven self-regulation.

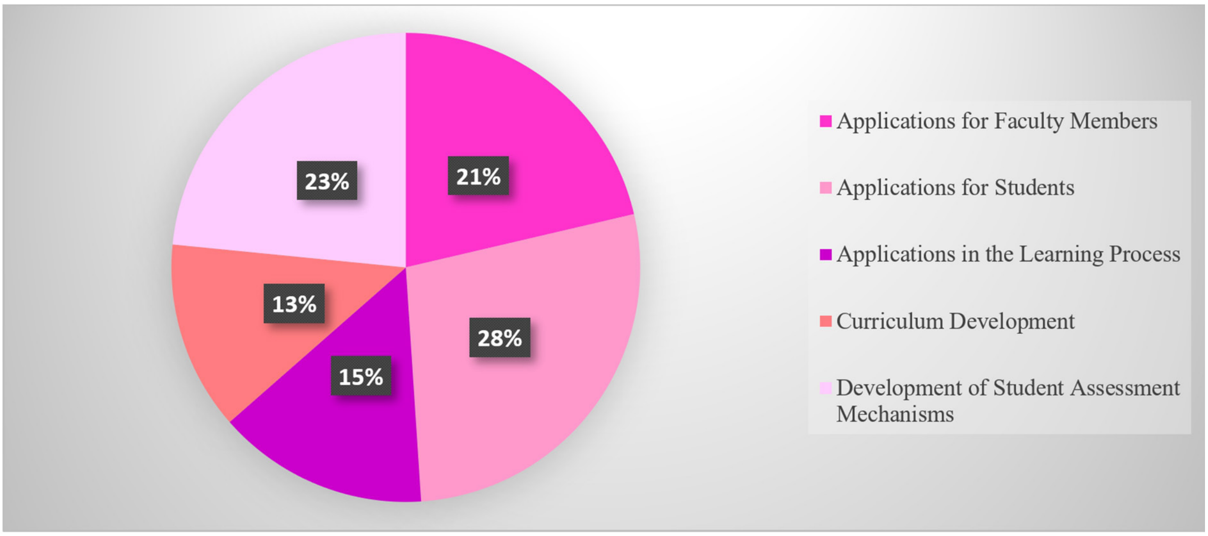

Figure 2: Visual summary of findings

The second largest share (23%) is attributed to *Development of Student Assessment Mechanisms*, reflecting the increasing use of data-driven, real-time, differentiated evaluation methods. *Applications for Faculty Members* (21%) highlight the pedagogical shift toward personalized instructional design and adaptive teaching practices supported by learner analytics. *Applications related to the Learning Process* (15%) and *Curriculum Development* (13%) represent smaller portions of the distribution but remain important, demonstrating the development of responsive learning environments and flexible curricular structures.

Overall, the distribution of these categories illustrates that personalized learning is not limited to learner autonomy; it also requires a systemic reconfiguration of instructional roles, assessment practices, and curricular design, factors with significant implications for transforming the medical education system.

Discussion

Since AI began to be integrated into medical education, there has been a shift toward more personalized, adaptive, and data-informed approaches to teaching and learning (45, 46). Findings from the meta-synthesis reveal that AI applications are transforming medical education in multiple ways, including the provision of real-time learner analytics and feedback loops that enable instructors to respond more effectively to individual student needs, as well as supporting inclusive instructional practices designed to address learner diversity across instruction and assessment. In addition to changes in learners' educational experiences, the data also indicates shifts in faculty instructional practices, curricular structures, and assessment mechanisms. Furthermore, synthesis of student-focused concepts within the meta-analysis highlights a growing recognition of the importance of enabling personalized learning to support students with diverse backgrounds, competencies, and aspirations in contemporary medical education. The primary aim of this study was to synthesize existing research on the application of artificial intelligence to personalized education in the training of physicians and to organize this body of literature into analytically coherent categories with clear practical implications. The findings are structured around five major domains: 1) faculty applications; 2) student applications; 3) learning process applications; 4) curriculum development applications; and 5) student assessment applications. Understanding the potential for transformative change in medical education requires consideration of both the distinct contributions of each domain and the interrelationships among them.

(i) Applications for Faculty Members

In the development of personalized approaches to learning, faculty roles have shifted from a primary focus on knowledge transmission to the design of personalized learning experiences for individual learners. Faculty are now able to tailor instructional resources, provide varied forms of feedback, and implement diverse instructional strategies by identifying learner diversity through performance data analysis and the development of adaptive teaching models. In addition, personalized technologies have helped reduce the time faculty spend on real-time administrative tasks and have enhanced data-driven decision-making through the more effective and efficient use of educational resources. As a result of these educational transformations, the quality of teaching has improved, and alternative modes of communication between instructors and learners have emerged that better address individual learner needs.

Tetzlaff, et al. (47) developed a framework to guide educators in implementing an innovative model that reconceptualizes personalized learning as a dynamic, multilayered, and data-driven process. They argue that for personalization to be effective, learners' cognitive, motivational, and emotional characteristics must be continuously monitored in real time, with instructional adjustments made accordingly. As part of ongoing research related to personalized learning, Reber, et al. (48) proposed a framework for fostering students' interest in mathematics and science. They describe how academic interest typically develops from situational interest into more stable, individualized interest when appropriate support is provided. To facilitate this transition, they identify three types of interventions: context personalization, example choice, and active personalization. Evidence indicates that these interventions can enhance situational interest and behavioral engagement among students with initially low levels of either and, in some cases, promote sustained individual interest.

Building on prior work in this area, Tang, et al. (49) developed a model of personalized STEM education centered on self-regulated learning, using analyses of learner behaviors on online platforms to generate customized learning recommendations. Data mining and machine learning algorithms are incorporated into this approach to support core self-regulatory processes, including planning, monitoring, and self-evaluation. These findings are consistent with a growing body of research on the personalization of education (20, 21, 24, 25, 27–34).

(ii) Applications for Students

Personalized learning through the creation of customized learning pathways is one of the most visible manifestations of personalization in education. These learning pathways are developed based on the learners' educational background, cognitive style, personal interests, and career aspirations, and are intended to promote greater awareness of the learners' own learning processes, self-regulation, and responsibility for learning. In addition to enhancing motivation and deeper comprehension of learning material, personalized learning supports the development of learners' capacity to make informed decisions about their educational and career pathways. In this context, the use of real-time feedback, progress tracking, and individualized instruction has fostered learner-centered environments in which students are positioned at the core of the instructional process.

Wu, et al. (50) demonstrated that tailoring content, pace, and assessment to individual learner characteristics can substantially improve instructional effectiveness. Analyses based on behavioral and cognitive data illustrate how dynamic learning systems can accommodate the learners' unique differences, including learning styles, prior knowledge, and preferences in responding to instructional materials. This approach is particularly relevant in medical education, where learners must master complex and specialized content, often of a clinical nature, which requires active engagement, strong self-regulation, and individualized learning trajectories. Similarly, the implementation of intelligent learning systems has been shown to increase student interaction, promote self-regulated learning, and improve academic performance (51). By aligning instructional content with students' interests, experiences, and personal goals (52), Vorobyeva et al. demonstrated increases in engagement across motivational, cognitive, and behavioral dimensions (53). Finally, Ellikkal, et al. (53) illustrated how recommender systems can facilitate individualized learning experiences based on the learners' cognitive and behavioral characteristics. Collectively, these findings are consistent with and support the broader literature on personalized learning (20-25, 27-35).

(iii) Applications in the Learning Process

Recent advances in teaching and learning have necessitated new approaches within contemporary learning environments. Instructional design theory should emphasize instructional activities informed by data derived from both behavioral and cognitive assessments of learners. Cognitive load can be managed through the provision of individualized learning pathways. Creating opportunities for learners to engage in meaningful learning experiences, such as group activities, clinical simulations, and individualized projects, represents a critical component of this transformation. Learning within these environments is not solely cognitive in nature but also emotional, social, and experiential.

Alqahtani, et al. (54) suggest that the integration of artificial intelligence technologies into learning environments has the potential to transform instructional design and delivery. Adaptive learning pathways can be developed through the application of machine learning algorithms and behavioral data analysis. Moreover, adaptive learning technologies enable support to be provided to individual learners at their point of need. Through the implementation of such approaches, learners demonstrate increased engagement and self-regulation, while responsive and individualized learning environments are established. These developments also promote new forms of interaction between students and instructors that align with the learners' styles, needs, and personal goals (55).

Furthermore, Fitria (56) reports that AI-supported systems can address a wide range of learner needs in the classroom and enhance the quality of learner–instructor interactions. By identifying learner behaviors, recognizing preferred learning modalities, and delivering targeted content, AI technologies can support more effective and efficient instruction. Collectively, these findings align with and support the broader literature on AI-enabled personalized learning (20-34).

(iv) Curriculum Development

Curriculum-level personalization involves aligning education with each learner's unique needs, interests, and career aspirations to create curricula that effectively address those needs. This approach requires the design of educational programs informed by analyses of learning styles, learning performance, and other individual learner characteristics. Examples include the use of flexible digital content, customizable modules, and authentic, individualized projects embedded within the curriculum. Personalized curricula are typically developed using multifaceted, non-linear structures that provide learners with opportunities for gradual, varied, and intensive levels of learning. Collaboration in the curriculum design process, such as incorporating student input and co-developing course materials, actively engages learners and fosters a sense of ownership and cognitive engagement, thereby increasing the likelihood of long-term knowledge retention. According to Gerard, et al. (57), personalizing curriculum development is an effective strategy for addressing individual learner differences. They reported that well-designed curricula aligned with students' learning styles, interests, prior knowledge, and academic objectives enhance engagement with the learning process, improve conceptual understanding, and foster a stronger sense of belonging. In a global survey study, Abbasi, et al. (58) argued that AI tools could assess learner-specific needs and provide real-time feedback, thereby supporting the development of critical thinking skills and facilitating more flexible, goal-directed curricula. Tavakoli, et al. (59) proposed an alternative approach to curriculum personalization through the integration of crowdsourcing and AI. Their four-level framework enables the continuous development and refinement of personalized curricula based on collective learner input and encompasses learning objectives, skills, topic content, and learning packages. Collectively, these findings support prior research on curriculum personalization (20, 21, 24-27, 29-32).

(v) Development of Student Assessment Mechanisms

Assessment has traditionally been used as a tool to measure knowledge acquisition; however, it is increasingly being integrated as a core component of the learning process. The use of real-time graphical feedback and analysis of student performance data enables the linkage of evidence from individual learning outcomes to the development of personalized learning pathways based on prior performance. Examples of such assessment approaches include adaptive assessments, real-world assessment tasks grounded in authentic professional practice, and self-assessment models that allow students to evaluate their own performance. The application of artificial intelligence and machine learning enables more accurate identification of students' strengths and weaknesses, thereby supporting the development of efficient and individualized learning pathways. Accordingly, assessment functions not only as a means of differentiation among learners but also as a mechanism for professional development, critical thinking, and enhanced decision-making. According to Hooda, et al. (60), machine learning technologies allow instructors to continuously monitor student performance throughout a course and to provide proactive support through early interventions for learners who may be struggling. Recent research suggests that AI has the potential to enhance the quality of higher education by improving learning experiences for students. Jani, et al. (61) demonstrated how intelligent algorithms could be effectively used to generate feedback, conduct assessments, and support formative evaluation processes. Their findings indicated that structured checklists combined with machine learning techniques enabled effective monitoring of student's progress and facilitated the identification of areas in clinical performance requiring improvement. Similarly, Samarakou, et al. (62-64) examined the role of artificial intelligence in continuous assessment and learner support for engineering students using the StuDiAsE (Student Diagnosis, Assistance, Evaluation) system. Their results showed that AI systems could provide individualized feedback and assess student performance using both qualitative and quantitative indicators. These findings are consistent with previous studies on AI-supported assessment practices (20, 21, 23-34).

Limitations and Future Directions

The principal limitation of this investigation is its focus solely on English-language publications published between 2010 and 2025. As a result, relevant literature published in other languages or addressing different time periods may have been excluded. In addition, grey literature (e.g., technical reports, student theses) was not included, which may limit the identification of emerging perspectives or innovative applications. Another limitation is variability in how the concept of "personalized learning" and associated AI applications are defined and operationalized across the literature, including differences in definitions and measurement approaches. This variability makes direct comparison and synthesis of the findings across studies challenging. Future investigations should employ experimental and longitudinal research designs to more rigorously assess the effectiveness of AI in supporting personalized learning across diverse educational settings. Further research should also explore hybrid (human–machine) instructional approaches in clinical education, develop robust indicators for measuring equity in personalized learning environments, and apply machine learning techniques to examine academic and career pathways. Collectively, these directions would support the continued integration of AI in medical education and contribute to improving both the quality and effectiveness of training programs.

Conclusion

In this research, a meta-synthesis was conducted using a structured framework designed to identify, categorize, and consolidate previous evidence regarding the types of artificial intelligence applied to personalized learning in medical education. The findings indicate that AI-driven personalization, in combination with technologies such as large language models, virtual reality, and real-time learning analytics, enables alignment of educational processes with the learners' cognitive styles, goals, and prior knowledge, while simultaneously redefining the role of faculty from transmitters of knowledge to adaptive designers of learning experiences. This evolving role creates opportunities to enhance learners' self-regulation, motivation, and clinical reasoning, as well as to support evidence-informed educational and career development pathways. The results further demonstrate that personalization occurs across multiple levels, influencing curriculum design, assessment practices, and the configuration of educational technologies within diverse teaching and learning environments. Accordingly, educational institutions should employ data-mining techniques, adopt adaptive algorithms, and provide real-time feedback to learners to develop inclusive and equitable learning ecosystems. In addition to synthesizing findings from previously conducted studies and generating new insights through an innovative conceptual model of AI-enabled personalization, the conceptual and policy framework developed through this meta-synthesis may serve as a guide for the ethical and equitable governance of AI-enabled personalization. This framework includes recommendations for curriculum redesign, adaptive assessment strategies, and faculty development initiatives. Collectively, the findings of this study not only integrate existing research but also provide a roadmap for theory, policy, and practice with the potential to transform the future delivery of medical education.

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Authors' Contributions

M.H contributed to data collection. A.K performed data analysis. Z.F assessed the quality of the articles and wrote the initial draft. AT.M contributed to translation and final manuscript writing. A.K was the principal supervisor of the entire research process. All authors reviewed the final manuscript.

Conflicts of interest

The authors declare no conflicts of interest.

Declaration of AI Use

The authors used AI tools to translate and summarize some articles. All AI-generated outputs have been reviewed and approved by all authors. The authors assume full responsibility for the final content.

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