Ensuring equitable access to artificial intelligence in medical education: a scoping review

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Abstract

Purpose – Artificial intelligence (AI) is transforming medical education, enhancing knowledge acquisition, teaching, assessment, and curriculum delivery. While AI offers the potential to democratise access and improve inclusivity, little is known about how equity is addressed in AI-enabled medical education. This scoping review maps current evidence, identifies gaps, and provides insights for equitable implementation.

Design/methodology/approach – A scoping review was conducted following the Joanna Briggs Institute methodology. Peer-reviewed literature was identified through MEDLINE, Evidence-Based Medicine Reviews (Health Technology Assessment), Health and Psychosocial Instruments and Global Health. Screening, data extraction, and thematic analysis were performed by multiple reviewers. Quantitative data were summarised descriptively, and qualitative data were synthesised to identify narrative themes.

Findings – Of 256 records identified, 80 full-text articles were reviewed, and 35 studies were included. Most were published between 2022 and 2025 and originated predominantly from high-income countries. AI applications focused on large language models (48%), with curriculum design (49%) being the most common area of focus. Equity themes were: (1) equitable access (demographic, geographic, and distributed learning disparities); (2) bias (algorithmic, cultural, and socioeconomic); and (3) AI literacy (limited curricular exposure and preparedness).

Originality/value – Previous literature reviews have examined AI and its ethical use in medical education, but not through an equity lens. This scoping review highlights that medical education is at a pivotal juncture, shaped by converging imperatives: inclusivity and the rapid evolution of AI. To expand access and standardisation, equitable implementation requires AI literacy, contextually relevant tools, and active bias mitigation. Future research should prioritise inclusive, contextually appropriate, and accessible AI interventions across medical education.

Keywords Artificial intelligence, Medical education, Equity, Access, Widening access, Underrepresented population groups, AI literacy

Paper type Literature review

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1. Introduction

Artificial intelligence (AI) is rapidly transforming how both healthcare and medical education are delivered (Ahsan, 2025; Duan *et al.*, 2025; Greengrass, 2024). Over the past decade, AI has evolved from early adoption to become an embedded, accepted, and integral component of medical education (Gordon *et al.*, 2024). Currently, AI is used across many areas, including student selection, knowledge acquisition, teaching modalities, assessment, curriculum design and delivery, and administrative processes (Duan *et al.*, 2025; Gordon *et al.*, 2024). AI is not only a transformative tool for teaching and learning, but a core competency that future medical practitioners need to master (Greengrass, 2024).

Several broad scoping and narrative literature reviews have examined how AI is being applied and its ethical use in medical education (Ahsan, 2025; Gordon *et al.*, 2024; Rincón *et al.*, 2025). However, few have focused on issues surrounding equitable access. Gordon *et al.* (2024) emphasised the importance of collaboration between educators, policymakers, and AI developers to ensure “AI tools are available to all without bias” (Gordon *et al.*, 2024). Despite this, their review did not explicitly evaluate included studies through an equity lens (Gordon *et al.*, 2024). Similarly, Ahsan *et al.* (2025) and Rincón *et al.* (2025) did not focus on equity but raised concerns that AI favours high-resource settings, exacerbating existing disparities in medicine and widening the gap for underrepresented groups (Ahsan, 2025; Rincón *et al.*, 2025). Key issues included limited technological infrastructure, financial constraints, biased datasets, poor connectivity in rural areas and limited support for educators and students in effective use (Ahsan, 2025; Akefe *et al.*, 2025; Rincón *et al.*, 2025). However, if purposefully implemented, with attention to geographical needs, resource availability and cultural context, AI has the capacity to enhance and democratise accessibility and equity in medical education (Ahsan, 2025; Bray *et al.*, 2025; Rincón *et al.*, 2025).

Equity is the state in which everyone has a fair and just opportunity (Organisation for Economic Co-operation and Development, 2012). Efforts to create a more equitable medical profession have led to strategies aimed at widening access and participation for diverse, underrepresented, and disadvantaged groups to study medicine (Fuller *et al.*, 2025; George *et al.*, 2025). These strategies vary and are shaped by unique cultural, geographic, economic and political contexts (George *et al.*, 2025). Educating a more diverse cohort of medical professionals will help to ensure the workforce is representative of the communities they serve, which is anticipated to address workforce shortages and enhance health outcomes (Fuller *et al.*, 2025; George *et al.*, 2025). Widening access and participation are two separate yet interconnected concepts; widening access refers to reducing barriers to admission to medical school (opening the door), while widening participation ensures that the medical education is delivered in an inclusive teaching environment, which is accessible and appropriate for diverse and underrepresented populations (Akefe *et al.*, 2025; Case, 2025; George *et al.*, 2025).

AI offers the potential to widen access and participation in medicine by enhancing learning opportunities and making education more inclusive across diverse contexts (Ahsan, 2025; Akefe *et al.*, 2025). Yet, despite its promise, there remains a limited literature synthesis addressing equitable access within AI-enabled medical education. This scoping review seeks to map existing approaches, therefore, identify gaps, and generate insights that can guide equitable implementation across a range of educational, cultural, and geographic settings.

2. Methods

This paper followed the Joanna Briggs Institute scoping review methodology, which is grounded in the foundational work of Askey and O’Malley (2005) and subsequently refined by Levac *et al.* (2010) (Arksey and O’Malley, 2005; Levac *et al.*, 2010; M. Peters *et al.*, 2024). The methodology comprised a five-step process (1) identifying the research question, (2) identifying relevant studies, (3) study selection, (4) charting the data and (5) collating, summarising and reporting the results (Arksey and O’Malley, 2005; Levac *et al.*, 2010; M. Peters *et al.*, 2024).

2.1 Identifying the research question

The scoping review aimed to capture a breadth of literature; hence, the broad question "what is known regarding equitable access to AI and medical education" was used to develop the search strategy.

The eligibility/inclusion criteria were defined using the PCC (Population, Concept, Context) framework, as recommended for scoping reviews (Aromataris and Munn, 2019).

(1) Population: Medical undergraduate or medical postgraduate degree (pre-professional registration).

(2) Concept: Equitable access to AI in medical education.

(3) Context: Any setting related to tertiary or higher education institutions globally, providing training to become a medical practitioner (pre-professional registration).

2.2 Identifying the relevant studies

A comprehensive search strategy was developed to identify relevant peer-reviewed literature. The final search was conducted on August 27, 2025, across four major electronic databases: MEDLINE, Evidence-Based Medicine Reviews–Health Technology Assessment, Health and Psychosocial Instruments and Global Health. These databases were selected for their broad coverage of medical education literature.

The search strategy included a combination of controlled vocabulary (e.g. MeSH terms) and free-text terms. Keywords included, but were not limited to:

(1) *"Equity"*

(2) *"Access"*

(3) *"Medical Education"*

(4) *"Artificial Intelligence"*

Boolean operators (AND, OR) were used to combine search terms, and filters were applied to limit results to English-language publications. No date restrictions were applied to ensure the inclusivity of older foundational studies, as well as recent developments.

The inclusion and exclusion criteria used for study selection are summarised in Table 1.

The full search strategy, including specific database queries, is available in the Supplementary Material (Appendix).

2.3 Study selection

All search results were exported into a reference management software (EndNote) (Clarivate, 2023), duplicates were removed and thereafter exported to Covidence (Veritas Health Innovation, 2021). Title and abstract screening were conducted independently by two reviewers (JB and NW) using the predefined eligibility criteria (Table 1). If consensus could not be reached at this stage, the full text was reviewed.

For studies deemed potentially relevant, the full texts were retrieved and assessed for inclusion (JB, NW, CC, CM, JM, EM). Discrepancies during the full-text screening stage were resolved through discussion with a third reviewer (JB, JM, CM), who provided an independent opinion to ensure consistency and reduce bias.

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) flow diagram illustrates the study selection process, including the number of records identified, screened, included, and excluded, along with the reasons for exclusion (Tricco *et al.*, 2018) (Figure 1).

Table 1. Scoping review inclusion and exclusion criteria

	Inclusion	Exclusion
Population	Medical undergraduate or medical postgraduate degree students (pre-professional registration) Faculty in medical undergraduate or medical postgraduate degrees Supervisors of medical undergraduate or medical postgraduate degree students	Study participants who are not involved in a medical undergraduate or medical postgraduate degree (pre-professional registration)
Concept	Equity and access to AI in medical education	Access when not presented through an equity lens
Context	Medical undergraduate or medical postgraduate degree (pre-professional registration)	Medical education post professional registration Health education that does not include medical education
Other	Original studies	Reviews Studies not in English

2.4 Data charting and extraction

A standardised data charting form was developed and piloted across a sample of five studies to ensure clarity and relevance. The charting process was iterative and flexible, allowing for the refinement of data items as familiarity with the literature deepened. The authors collaboratively reviewed and agreed upon the final data extraction table.

The following data were extracted from each study: Bibliographic information, study design and methodology, geographic location and institutional context, study population characteristics, type of AI, and context of AI and equity in medical education.

All data were independently extracted by one reviewer (JB) and cross-verified for accuracy by other reviewers (JM, NW). Any inconsistencies were resolved through consensus or consultation with a third reviewer.

2.5 Collating, summarising, and reporting the results

Quantitative and qualitative analyses were undertaken to collate and map the data. Descriptive statistics were used to collate the quantitative data. Qualitative thematic analysis was employed to develop relevant themes to address the objective of the scoping review. Notable patterns, facilitators, barriers, and research gaps were highlighted to inform future research directions and policy implications. Given the scoping nature of this review, no formal quality appraisal or risk of bias assessment was conducted (Peters *et al.*, 2024).

3. Results

The search results yielded 256 studies for full-text screening (August 2025), with one duplicate removed (Figure 1). After abstract and title screening, 80 studies remained for full-text review. Following further evaluation against the inclusion and exclusion criteria, 45 studies were excluded. The primary reason for exclusion was the absence of a focus on equity ($n = 23$). Other reasons included ineligible population group ($n = 7$), ineligible study design ($n = 5$), ineligible population setting ($n = 3$), outcomes did not align with the focus ($n = 3$), was not original research ($n = 3$), and intervention was outside the inclusion criteria ($n = 1$) (Figure 1).

3.1 Study characteristics

Table 2 presents a quantitative description of the included studies. Of the studies reviewed, 97% ($n = 34$) were published between 2022 and 2025, with 51% ($n = 18$) in 2025. The studies

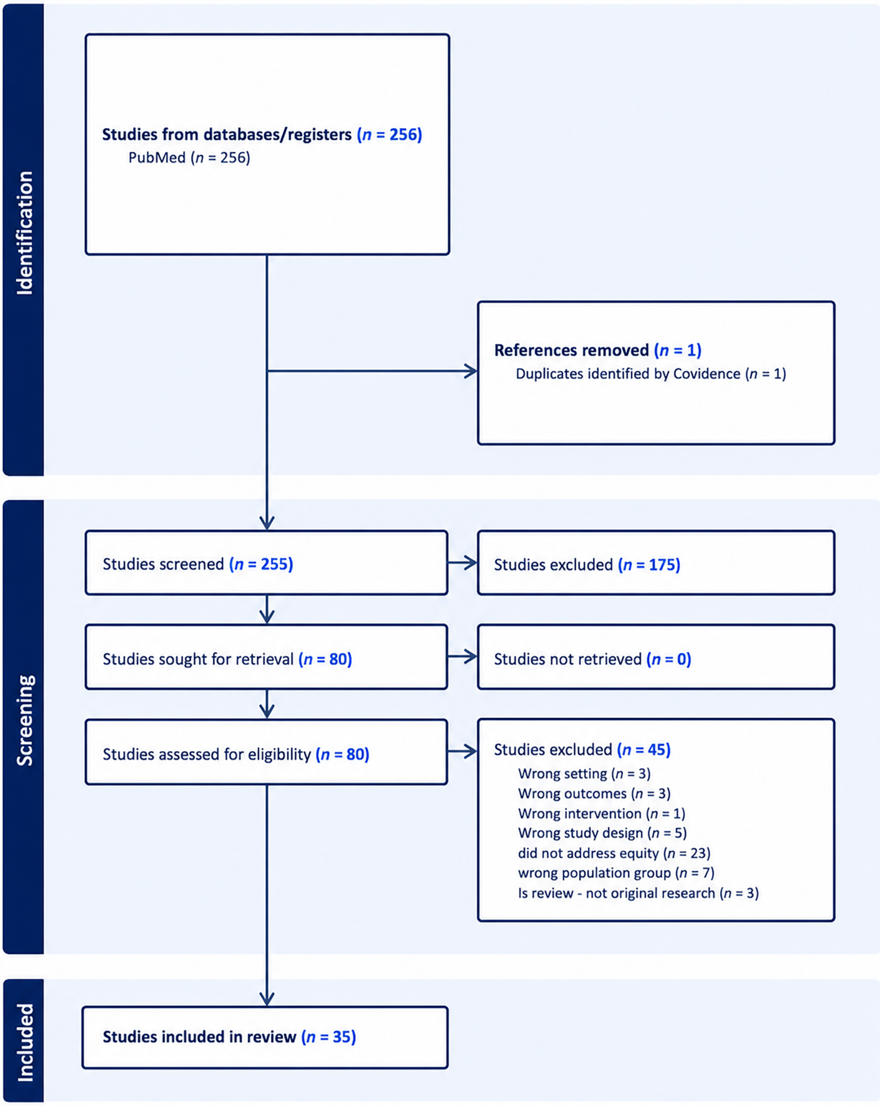

Figure 1. Preferred Reporting Items for Systematic Reviews and Meta Analysis extension for scoping reviews (PRISMA-Scr)

originated from 16 countries, with the largest proportion (40%, $n = 14$) from the United States of America (USA). India contributed the second-highest number of studies (14%, $n = 5$). Notably, 66% of the countries were represented by a single study (Figure 2).

A variety of study methodologies were employed, with 29% ($n = 10$) case-based or educational intervention studies. The next most common methodology was comparative performance/observational studies (23%, $n = 8$), followed by commentary/perspective pieces (20%, $n = 7$). Most studies (54%, $n = 19$) involved participant-based research, with "medical students only" being the most studied group (37%, $n = 13$).

Table 2. Studies' characteristics

Variable	Percentage ($N = 35$)
Year of publication	2002 3% (1) (Caudell *et al.*, 2003) 2022 3% (1) (Spear *et al.*, 2022) 2023 14% (5) (Biri *et al.*, 2023; Ma *et al.*, 2023; Scherr *et al.*, 2023; Shimizu *et al.*, 2023; Spallek *et al.*, 2023) 2024 29% (10) (Cherif *et al.*, 2024; Divito *et al.*, 2024; Jebreen *et al.*, 2024; Kıyak and Kononowicz, 2024; Meyer *et al.*, 2024; Mondal *et al.*, 2024; Noel, 2024; Robleto *et al.*, 2024; Sauder *et al.*, 2024; Xu *et al.*, 2024) 2025 51% (18) (Abouammoh *et al.*, 2025; Ahmed *et al.*, 2025; Bray *et al.*, 2025; Gin *et al.*, 2025; Jagannath *et al.*, 2025; Laverde *et al.*, 2025; Mashburn *et al.*, 2025; Mishra *et al.*, 2025; Mondal, 2025; Monzon and Hays, 2025; Mukadam *et al.*, 2025; Pu *et al.*, 2025; Rueff *et al.*, 2025; Sharma *et al.*, 2025; Smirnova *et al.*, 2025; Sunmboye *et al.*, 2025; Theros *et al.*, 2025; Yli-Hallila *et al.*, 2025)
The primary country of study originated from	Australia 3% (1) (Spallek *et al.*, 2023) Canada 3% (1) (Smirnova *et al.*, 2025) China 6% (2) (Ma *et al.*, 2023; Pu *et al.*, 2025) Colombia 3% (1) (Laverde *et al.*, 2025) Finland 3% (1) (Yli-Hallila *et al.*, 2025) Germany 6% (2) (Mashburn *et al.*, 2025; Meyer *et al.*, 2024) India 15% (5) (Biri *et al.*, 2023; Mishra *et al.*, 2025; Mondal, 2025; Mondal *et al.*, 2024; Sharma *et al.*, 2025) Japan 3% (1) (Shimizu *et al.*, 2023) Palestine 3% (1) (Jebreen *et al.*, 2024) Saudi Arabia 3% (1) (Abouammoh *et al.*, 2025) Sudan 3% (1) (Ahmed *et al.*, 2025) Tunisia 3% (1) (Cherif *et al.*, 2024) Turkey and Poland 3% (1) (Kıyak and Kononowicz, 2024) United Kingdom 6% (2) (Mukadam *et al.*, 2025; Sunmboye *et al.*, 2025) United States of America 40% (14) (Bray *et al.*, 2025; Caudell *et al.*, 2003; Divito *et al.*, 2024; Gin *et al.*, 2025; Jagannath *et al.*, 2025; Monzon and Hays, 2025; Noel, 2024; Robleto *et al.*, 2024; Rueff *et al.*, 2025; Sauder *et al.*, 2024; Scherr *et al.*, 2023; Spear *et al.*, 2022; Theros *et al.*, 2025; Xu *et al.*, 2024)
Types of studies	Case based or Educational Intervention Studies 29% (10) (Caudell *et al.*, 2003; Jagannath *et al.*, 2025; Mukadam *et al.*, 2025; Rueff *et al.*, 2025; Sauder *et al.*, 2024; Scherr *et al.*, 2023; Spear *et al.*, 2022; Theros *et al.*, 2025; Xu *et al.*, 2024; Yli-Hallila *et al.*, 2025) Comparative Performance/Observational study 23% (8) (Cherif *et al.*, 2024; Laverde *et al.*, 2025; Mashburn *et al.*, 2025; Meyer *et al.*, 2024; Noel, 2024; Pu *et al.*, 2025; Robleto *et al.*, 2024; Smirnova *et al.*, 2025) Commentary/Perspective 20% (7) (Bray *et al.*, 2025; Divito *et al.*, 2024; Kıyak and Kononowicz, 2024; Mishra *et al.*, 2025; Mondal, 2025; Mondal *et al.*, 2024; Spallek *et al.*, 2023) Cross sectional survey 11% (4) (Ahmed *et al.*, 2025; Biri *et al.*, 2023; Ma *et al.*, 2023; Sunmboye *et al.*, 2025) Educational Intervention 3% (1) (Monzon and Hays, 2025) Mixed methods descriptive study 3% (1) (Jebreen *et al.*, 2024) Qualitative 11% (4) (Abouammoh *et al.*, 2025; Gin *et al.*, 2025; Sharma *et al.*, 2025; Shimizu *et al.*, 2023)

(*continued*)

Table 2. Continued

Variable	Percentage (N = 35)
Study participants	Medical students only 37% (13) (Ahmed *et al.*, 2025; Biri *et al.*, 2023; Cherif *et al.*, 2024; Jagannath *et al.*, 2025; Jebreen *et al.*, 2024; Ma *et al.*, 2023; Mukadam *et al.*, 2025; Robleto *et al.*, 2024; Rueff *et al.*, 2025; Sharma *et al.*, 2025; Sunmboye *et al.*, 2025; Xu *et al.*, 2024; Yli-Hallila *et al.*, 2025) Medical students, faculty, and supervisors 17% (6) (Abouammoh *et al.*, 2025; Gin *et al.*, 2025; Mashburn *et al.*, 2025; Pu *et al.*, 2025; Shimizu *et al.*, 2023; Spear *et al.*, 2022) No participants 46% (16) (Bray *et al.*, 2025; Caudell *et al.*, 2003; Divito *et al.*, 2024; Kıyak and Kononowicz, 2024; Laverde *et al.*, 2025; Meyer *et al.*, 2024; Mishra *et al.*, 2025; Mondal, 2025; Mondal *et al.*, 2024; Monzon and Hays, 2025; Noel, 2024; Sauder *et al.*, 2024; Scherr *et al.*, 2023; Smirnova *et al.*, 2025; Spallek *et al.*, 2023; Theros *et al.*, 2025)
Artificial Intelligence in studies* (Multiple AI types may be included within a single study n = 48)	Diagnostic AI 4% (2) (Gin *et al.*, 2025; Robleto *et al.*, 2024) Nonspecific AI (general) 4% (2) (Jagannath *et al.*, 2025; Sunmboye *et al.*, 2025) Generative AI 10% (5) (Gin *et al.*, 2025; Monzon and Hays, 2025; Noel, 2024; Rueff *et al.*, 2025; Shimizu *et al.*, 2023) Machine Learning 15% (7) (Jebreen *et al.*, 2024; Ma *et al.*, 2023; Robleto *et al.*, 2024; Sharma *et al.*, 2025; Spear *et al.*, 2022; Theros *et al.*, 2025; Yli-Hallila *et al.*, 2025) Large Language Models 48% (23) (Abouammoh *et al.*, 2025; Ahmed *et al.*, 2025; Biri *et al.*, 2023; Bray *et al.*, 2025; Cherif *et al.*, 2024; Divito *et al.*, 2024; Gin *et al.*, 2025; Kıyak and Kononowicz, 2024; Laverde *et al.*, 2025; Mashburn *et al.*, 2025; Meyer *et al.*, 2024; Mondal, 2025; Mondal *et al.*, 2024; Monzon and Hays, 2025; Mukadam *et al.*, 2025; Pu *et al.*, 2025; Rueff *et al.*, 2025; Sauder *et al.*, 2024; Scherr *et al.*, 2023; Sharma *et al.*, 2025; Spallek *et al.*, 2023; Theros *et al.*, 2025; Xu *et al.*, 2024) Precision education 4% (2) (Bray *et al.*, 2025; Gin *et al.*, 2025) Simulated Patients/Virtual Reality 10% (5) (Bray *et al.*, 2025; Caudell *et al.*, 2003; Gin *et al.*, 2025; Laverde *et al.*, 2025; Mishra *et al.*, 2025) Personalised Learning 6% (3) (Bray *et al.*, 2025; Mishra *et al.*, 2025; Smirnova *et al.*, 2025)
Medical Education area of focus	Assessment 11% (4) (Cherif *et al.*, 2024; Kıyak and Kononowicz, 2024; Meyer *et al.*, 2024; Smirnova *et al.*, 2025) Clinical Decision making 3% (1) (Mashburn *et al.*, 2025) Curriculum 49% (17) (Divito *et al.*, 2024; Jagannath *et al.*, 2025; Jebreen *et al.*, 2024; Laverde *et al.*, 2025; Mishra *et al.*, 2025; Monzon and Hays, 2025; Mukadam *et al.*, 2025; Noel, 2024; Pu *et al.*, 2025; Robleto *et al.*, 2024; Rueff *et al.*, 2025; Sauder *et al.*, 2024; Scherr *et al.*, 2023; Shimizu *et al.*, 2023; Spallek *et al.*, 2023; Theros *et al.*, 2025; Yli-Hallila *et al.*, 2025) Distributed learning 14% (5) (Bray *et al.*, 2025; Caudell *et al.*, 2003; Mondal, 2025; Mondal *et al.*, 2024; Spear *et al.*, 2022) General focus 23% (8) (Abouammoh *et al.*, 2025; Ahmed *et al.*, 2025; Biri *et al.*, 2023; Gin *et al.*, 2025; Ma *et al.*, 2023; Sharma *et al.*, 2025; Sunmboye *et al.*, 2025; Xu *et al.*, 2024)

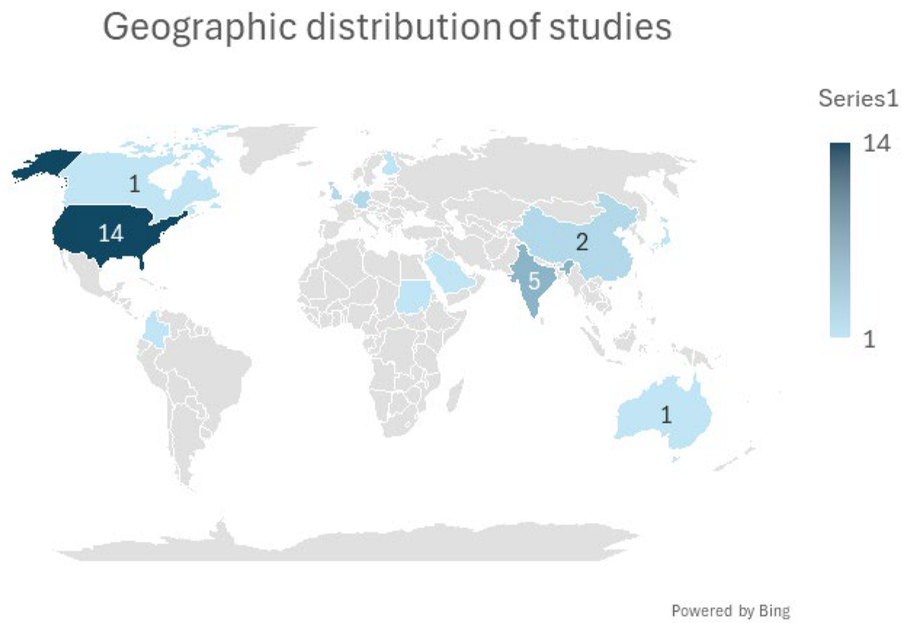

Figure 2. Global distribution of studies

The types of AI investigated were categorised into eight categories. As individual studies sometimes referenced more than one type of AI, a total of 48 instances of AI types were identified. Large Language Models (LLM), particularly iterations of ChatGPT, were the most common category (48%, $n = 23$) followed by Machine Learning (15%, $n = 7$).

The areas of medical education 21' studies most frequently addressed were curriculum-related topics (49%, $n = 17$), followed by general or non-specific themes (23%, $n = 8$), and distributed learning (14%, $n = 5$) (Table 2). Notably, only one study included an equity-related term (socio-economic disparities) in the study keywords (Monzon and Hays, 2025), and one included an equity-related term in the article title (disparities) (Mishra *et al.*, 2025) (Table 3).

3.2 Narrative analysis

Three overarching equity-related themes were identified across the included studies: (1) equitable access, (2) bias and (3) AI literacy and education, with many studies addressing multiple themes (Table 3, Figure 3). Within equitable access, sub-themes related to demographics (e.g. socioeconomic status, gender, culturally and linguistically diverse (CALD)) and geography (e.g. low resource settings, urban–rural disparities). Within bias, sub-themes centred on algorithmic bias (e.g. cultural appropriateness, under-representation of minority groups). AI literacy and education were underpinned by curriculum development. Across all themes, the literature highlighted facilitators and barriers, along with recommendations to support more equitable integration of AI into medical education.

3.3 Equitable access

Access through an equity lens was described as both a facilitator and a barrier to democratising medical education globally, with concepts of demographic, geographic, and distributed learning often overlapping.

3.3.1 Demographic access. Demographic access included gender, CALD and socio-economic measures such as income. Studies that focused on gender reported contrasting

Table 3. Study extraction data, authors, year, participant information and how equity was addressed

Authors, year, country of origin	Participant information	How equity was addressed
Abouammoh *et al.* (2025) Saudi Arabia	6 male medical students, 6 medical faculty (66% male)	• Cultural bias concerns about LLM. • Context-specific AI integration into the medical curriculum is required
Ahmed *et al.* (2025), Sudan	1,443 medical students from both public and private universities. (65.8% female)	• Examinations of AI engagement across demographics revealed that hearing about and using ChatGPT: less likely among females, lower-income students, and students with poor internet quality • Institutions to integrate AI tools like ChatGPT into the curriculum through fostering digital literacy • Equitable access achieved by strengthening infrastructure/resources in underserved areas (rural)
Biri *et al.* (2023), India	172 medical students (55.2% females, 43.6% males, and 1.2% preferred not to say)	• Students viewed LLMs as vital for improving learning, accessibility, and the quality of medical education in developing countries • LLMs emerged as valuable supplementary resources, particularly in low-resource settings
Bray *et al.* (2025), USA	No participants	• AI can democratise access to learning resources, standardise distributed learning, and personalise training in rural medicine's unique needs • Virtual patient simulations can expose learners to diverse patient populations and include clinical scenarios often limited in rural settings
Caudell *et al.* (2003), USA	No participants	• The primary objective of this project is to determine whether an immersive virtual environment can be developed to enhance human comprehension and support distributed learning • Further evaluation of emerging technologies, such as immersive virtual reality, is required to overcome geographic barriers
Cherif *et al.* (2024), Tunisia	244 third-year students	• ChatGPT showed limitations in handling content from non-Western institutions and non-English examinations, such as the French-language Tunisian exam, where its performance was lower than in English assessments
Divito *et al.* (2024), USA	No participants	• Free access to ChatGPT was a positive, but limited functionality and potential future cost increases raise concerns about equitable access in low-resource settings with limited computer or internet availability
Gin *et al.* (2025), USA	25 participants (learners 12%, faculty/institutional leaders 60%, and AI representatives 28%)	• AI to enable decentralised (distributed) teaching, described a "hub-and-spoke" model whereby learners at remote locations receive equivalent education • Adversarial training was recommended as a technique to identify and mitigate bias in AI model development

(*continued*)

Table 3. Continued

Authors, year, country of origin	Participant information	How equity was addressed
Jagannath *et al.* (2025), USA	357 international medical students (from 28 countries)	• Participation in a radiology course asynchronously rather than synchronously increases access for remote students in low-resource settings • There is an unmet need for AI education in medical education, as participants reported inadequate exposure to AI in their medical school curriculum
Jebreen *et al.* (2024), Palestine	349 medical students. (71.92% female, 29.23% living in the Gaza Strip)	• No universities had a formal AI program, due to funding shortages and a lack of material and technical support • Males had a higher perception score about AI in medical education than females • Living in Gaza Strip was raised as an access issue with limited internet and electricity
Kıyak and Kononowicz (2024), Turkey and Poland	No participants	• The use of a customised case-based MCQ generator can produce contextually relevant questions, thus addressing equity concerns • Equity in access can be improved through partnerships and funding that enable educators globally to benefit from advanced technology
Laverde *et al.* (2025), Colombia	No participants	• Virtual patient models provide scalable, personalised learning but are limited by development costs • Concerns about AI biases
Ma *et al.* (2023), China	2,122 medical students (51% female, from 467 colleges)	• Over 50% had completed digital health courses, though regional disparities persisted across China • A national initiative was recommended for the curriculum design of AI.
Mashburn *et al.* (2025), Germany	Two groups were included: ChatGPT (1) (n = 27) and a research group (2) (n = 32); only group 1 demographics reported (63% female, 88.2% medical students)	• Gender-specific problem-solving strategies were found in AI interactions, emphasising the importance of AI literacy • Understanding these gender-associated tendencies is essential for designing AI tools that accommodate diverse learning approaches
Meyer *et al.* (2024), Germany	No participants	• GPT-3.5's and GPT-4's medical proficiency were assessed, finding differences compared to other languages • AI accuracy varies by language, reflecting the dominance of languages more represented in training data
Mishra *et al.* (2025), India	No participants	• Commentary specifically focused on equity • Personalised learning can be achieved via online platforms, which is valuable in resource-limited settings with limited access to qualified instructors and up-to-date materials • By analysing performance data across contexts, AI can identify learning gaps and tailor instruction to regional health needs and student abilities

(*continued*)

Table 3. Continued

Authors, year, country of origin	Participant information	How equity was addressed
Mondal (2025), India	No participants	• Institutions should ensure that all students have equitable access to AI tools, regardless of socioeconomic status • Institutions should develop contextual resources and guidelines to educate students on AI, mitigating the digital divide that could disadvantage certain groups of students
Mondal *et al.* (2024), India	No participants	• The accuracy of ChatGPT in the MCQ on primary health care was seen as a decision support tool, assisting remote medical education • Despite finding a level of accuracy, LLMs are still reliant on the quality of the data on which they are trained
Monzon and Hays (2025), USA	No participants	• Concerns about bias, equity in access • Universities should implement AI equity policies • Only study to include an equity-related term in keywords (socio-economic disparities)
Mukadam *et al.* (2025), United Kingdom	27 regionally based medical students (59.3% female, from three universities)	• AI-based standardised patients can supplement learning, particularly for independent practice in regional areas • Enhances access as traditional standardised patient programs can be difficult to access due to logistical constraints and costs
Noel (2024), USA	No participants	• AI medical illustrations have the potential to enhance the field of anatomy education; however, none of the AI generators were able to produce illustrations that were deemed both detailed and accurate • It predicted that with more training, AI-powered text-to-image generators may be a cost-effective solution, especially for institutions with limited resources
Pu *et al.* (2025), China	128 participants (19.5% medical students, 53.2% residents, 27.3% physicians, 58.5% female)	• In participants' perceptions of AI, physicians had the highest willingness to customise GPT into teaching hospitals • This is important because in China, where teaching capacity varies, therefore, customised GPTs combined with traditional methods could help bridge the gap
Robleto *et al.* (2024), USA	73 first year medical students	• Students raised concerns around biases of AI models • To address students' recommended physician supervision of the AI was required
Rueff *et al.* (2025), USA	90 second-year medical students	• Adoption of policy recommendations for AI integration into curricula • In the study, funding was available to support all students' ability to access the paid AI version to ensure equitable access

(*continued*)

Table 3. Continued

Authors, year, country of origin	Participant information	How equity was addressed
Sauder *et al.* (2024), USA	No participants	• Faculty literacy is required about Generative AI to educate students on how it should be optimally used in medical education • A limitation of Generative AI is the bias of the algorithms
Scherr *et al.* (2023), USA	No participants	• ChatGPT-based clinical simulations provide a cost-effective and scalable way to bridge knowledge gaps, offering an equitable option to resource-intensive simulation centres
Sharma *et al.* (2025), India	66 medical students. (52% male)	• Students raised AI biases as a concern and unequal access • AI can complement human tasks by facilitating remote learning in areas with limited human resources
Shimizu *et al.* (2023), Japan	55 participants (89.1% faculty, 10.9% medical students, 90% male)	• Strengths, weaknesses, opportunity, and threats framework were developed for AI in medical school curricula • A positive finding was improved literacy in second languages
Smirnova *et al.* (2025), Canada	No participants	• Reshaping assessment in medical education with movement toward precision education to address each learner's needs and goals • AI in assessment viewed as a means to address systemic inequities
Spallek *et al.* (2023), Australia	No participants	• Viewpoint on whether GPT-4's outputs are accessible, unbiased, or include any potentially false or stigmatising language when writing text for diverse audiences • GPT-4 can tailor information to specific audiences, but limited training on some subpopulations may reduce accuracy and increase bias
Spear *et al.* (2022), USA	Medical students and other learners (700 visits to the site in 20 days)	• Addressed equity through providing access to students who were prohibited from being on-site at medical facilities during the pandemic • Example of an effective remote model that did not compromise learning but enhanced equity access
Sunmboye *et al.* (2025), United Kingdom	230 medical students (59% female)	• AI model highlighted that equitable AI integration must account for demographic and access-related factors • Disparities in access and cost of AI tools may exacerbate existing inequalities within the student populations • Medical schools should integrate AI literacy into their curricula, ensuring students can evaluate AI.
Theros *et al.* (2025), USA	No participants	• Concerns LLM algorithmic bias • AI education remains absent from most medical curricula • AI can democratise medical education, making it feasible for low-resource settings to teach foundational AI concepts without financial or technical barriers

(*continued*)

Table 3. Continued

Authors, year, country of origin	Participant information	How equity was addressed
Xu *et al.* (2024), USA	102 medical students (75.5% preclinical years)	• The utilisation of AI and LLM tools and perspectives on the current and future role of AI in medicine • Concerns about algorithmic bias of LLMs, as not trained on the most up-to-date data • Previous AI knowledge and exposure correlated with more conscientious use of these tools, such as cross-checking information • AI should be taught in the medical curriculum
Yli-Hallila *et al.* (2025), Finland	75 participants (79% medical students, 21% dentistry students)	• The AI tool serves learning in many kinds of environments and can bridge educational gaps and provide standardised resources globally • The results of this pilot demonstrated the feasibility of AI platform for sharing teaching material between partners

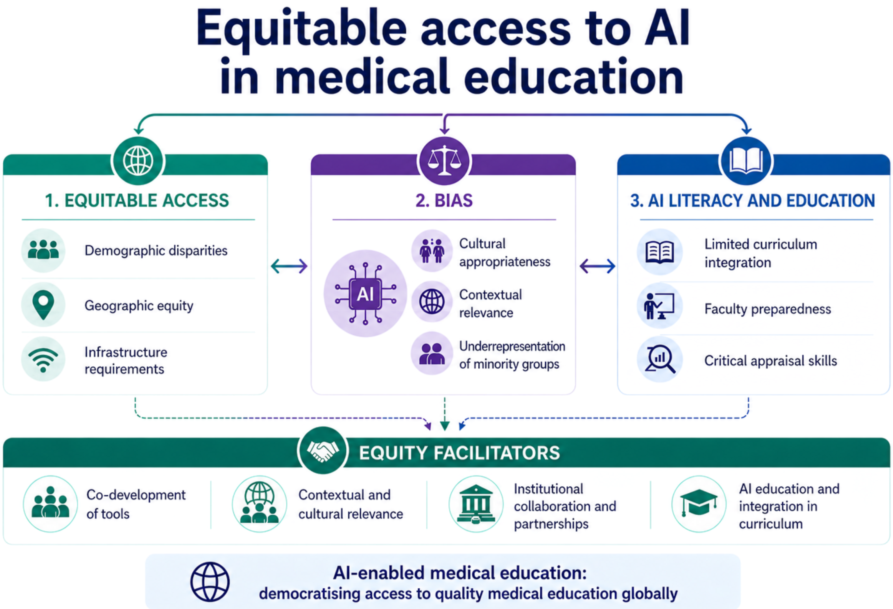

Figure 3. Conceptual framework of equity in AI enabled medical education

results (Ahmed *et al.*, 2025; Jebreen *et al.*, 2024; Mashburn *et al.*, 2025; Sunmboye *et al.*, 2025). Two studies conducted in low- and middle-income countries (LMICs) reported gender-related disparities, with female students demonstrating lower levels of knowledge and access to LLMs and reporting less favourable perceptions of AI compared to their male counterparts (Ahmed *et al.*, 2025; Jebreen *et al.*, 2024). In contrast, a German study found females had higher self-rated confidence after using an LLM compared to males and employed different problem-solving techniques, e.g. more fact checking of the LLM (Mashburn *et al.*, 2025). This latter finding was reinforced by a United Kingdom study that found female students exhibited a higher level of concern regarding inaccuracies in AI-generated content, and therefore were more likely to engage in behaviours aimed at mitigating these risks (Sunmboye *et al.*, 2025).

Access to AI for CALD populations was framed in two ways: by its ability to bridge existing educational divides, but also as a source of concern that it could exacerbate existing access inequities. One study stated English literacy as a major barrier, noting that English is the de facto standard academic language globally (Biri *et al.*, 2023). However, another study found that Generative AI facilitated more equitable access by successfully translating medical education resources into users' first language (Shimizu *et al.*, 2023). Despite this, other studies raised equity concerns due to LLMs lower accuracy on non-English examinations, reflecting their English-dominant training data and limited handling of linguistic nuances (Cherif *et al.*, 2024; Meyer *et al.*, 2024). AI has the potential to reduce medical education disparities for CALD populations, provided that issues of language accessibility and appropriateness are addressed and collaborative contextual adaptation of AI tools occurs (Jagannath *et al.*, 2025; Spallek *et al.*, 2023). For example, Spallek *et al.* (2023) highlight that when LLM educational resources are specifically developed for and co-designed with specific population groups, such as Aboriginal and Torres Strait Islander students in Australia, they have a higher acceptability and ability to meet their needs (Spallek *et al.*, 2023).

Costs surrounding AI were another conflicting concept (Ahmed *et al.*, 2025; Divito *et al.*, 2024; Rueff *et al.*, 2025; Scherr *et al.*, 2023). Medical students from low-socioeconomic backgrounds were found to be less likely to use LLMs (Ahmed *et al.*, 2025), with one study addressing this issue by providing funding so all students had equitable access to a subscription version of an LLM (Rueff *et al.*, 2025). It was noted that while some versions of LLM were cost-free, therefore more accessible, there were subscription versions of LLMs, which provide higher usage limits, and more sophisticated functionality. This may extend the divide amongst students based on their socio-economic background (Divito *et al.*, 2024; Scherr *et al.*, 2023).

3.3.2 Geographic access. Studies highlighted the presence of a medical education divide both between and within countries, with AI seen as a facilitator and barrier to the global standardisation of medical education (Biri *et al.*, 2023; Divito *et al.*, 2024; Jagannath *et al.*, 2025; Ma *et al.*, 2023; Mishra *et al.*, 2025; Mondal, 2025; Noel, 2024; Pu *et al.*, 2025; Theros *et al.*, 2025). Studies used terms such as developing countries (Biri *et al.*, 2023; Pu *et al.*, 2025), underdeveloped regions (Ma *et al.*, 2023), low-resource settings (Divito *et al.*, 2024; Jagannath *et al.*, 2025; Mishra *et al.*, 2025; Mondal *et al.*, 2024; Noel, 2024; Theros *et al.*, 2025) and rural areas (Ahmed *et al.*, 2025; Bray *et al.*, 2025) when describing geographic settings of interest. Collaboration and sharing of AI platforms between institutions with formal partnerships or open-access globally were deemed to be an important facilitator to bridging this divide (Jagannath *et al.*, 2025; Theros *et al.*, 2025; Yli-Hallila *et al.*, 2025). For example, one study described a virtual microscopy platform that was developed collaboratively and shared between institutions, providing an accessible standardised resource that had functionality for context-specific adaptation (Yli-Hallila *et al.*, 2025).

While the accessibility of AI tools was generally seen as positive, due to their low cost, availability of internet access, and the abundance of available information, this was not universal across geographic regions (Biri *et al.*, 2023; Divito *et al.*, 2024; Jebreen *et al.*, 2024; Kıyak and Kononowicz, 2024; Ma *et al.*, 2023; Mishra *et al.*, 2025; Mondal *et al.*, 2024; Noel, 2024; Pu *et al.*, 2025; Theros *et al.*, 2025; Yli-Hallila *et al.*, 2025). For example, Jebreen *et al.* (2024) surveyed Palestinian medical students' perceptions of AI in the curriculum, finding strong support for its inclusion but noting major barriers to its usage, due to limited access to technology, the internet, and electricity (Jebreen *et al.*, 2024).

Distributed learning was categorised by hub and spoke models, where AI-enabled centralised teaching was accessed by remote learners (Ahmed *et al.*, 2025; Bray *et al.*, 2025; Caudell *et al.*, 2003; Gin *et al.*, 2025; Mondal *et al.*, 2024; Mukadam *et al.*, 2025; Scherr *et al.*, 2023; Spear *et al.*, 2022). This model was particularly relevant in rural areas (Ahmed *et al.*, 2025; Bray *et al.*, 2025; Gin *et al.*, 2025; Mondal *et al.*, 2024), in geographically distributed partner institutions (Caudell *et al.*, 2003; Yli-Hallila *et al.*, 2025), and for locations without a simulation centre (Scherr *et al.*, 2023). It also addressed unequal access to a clinical setting during the COVID-19 pandemic (Spear *et al.*, 2022).

A common application of distributed learning was the use of virtual patient simulations (Ahmed *et al.*, 2025; Bray *et al.*, 2025; Caudell *et al.*, 2003; Mukadam *et al.*, 2025). These were described as an effective supplement to traditional educational methods when access to standardised patients was limited. This facilitated learner engagement with a diverse, yet contextually appropriate patient population and enabled them to practice clinical scenarios (Ahmed *et al.*, 2025; Mukadam *et al.*, 2025).

3.4 Biases and mitigation strategies

Concerns relating to AI perpetuating existing biases in medical education were commonly associated with LLMs exhibiting algorithmic bias (Abouammoh *et al.*, 2025; Bray *et al.*, 2025; Cherif *et al.*, 2024; Gin *et al.*, 2025; Kıyak and Kononowicz, 2024; Laverde *et al.*, 2025; Ma *et al.*, 2023; Mashburn *et al.*, 2025; Meyer *et al.*, 2024; Monzon and Hays, 2025; Robleto *et al.*, 2024; Sauder *et al.*, 2024; Scherr *et al.*, 2023; Sharma *et al.*, 2025; Smirnova *et al.*, 2025; Spallek *et al.*, 2023; Theros *et al.*, 2025; Xu *et al.*, 2024). The type of algorithmic bias was not always transparently described (Monzon and Hays, 2025; Sauder *et al.*, 2024; Sharma *et al.*, 2025; Theros *et al.*, 2025; Xu *et al.*, 2024). However, when specified, biases included cultural (Abouammoh *et al.*, 2025; Laverde *et al.*, 2025; Meyer *et al.*, 2024; Robleto *et al.*, 2024; Spallek *et al.*, 2023), geographic (Bray *et al.*, 2025; Cherif *et al.*, 2024), gender (Laverde *et al.*, 2025; Spallek *et al.*, 2023), social (Laverde *et al.*, 2025; Ma *et al.*, 2023; Mashburn *et al.*, 2025; Robleto *et al.*, 2024; Scherr *et al.*, 2023) and age and disability (Robleto *et al.*, 2024).

In AI-enhanced medical education, biases may emerge in contexts such as using LLMs to generate multiple-choice questions (Kıyak and Kononowicz, 2024), develop virtual patient chatbots (Laverde *et al.*, 2025) and student self-directed learning (Meyer *et al.*, 2024; Spallek *et al.*, 2023). In studies that surveyed medical students about their perceptions of AI, concerns about the existence of biases were common, although detailed explanations were rarely provided (Abouammoh *et al.*, 2025; Cherif *et al.*, 2024; Mashburn *et al.*, 2025; Robleto *et al.*, 2024; Sharma *et al.*, 2025; Xu *et al.*, 2024).

Studies included recommendations on strategies to mitigate biases; these included raising students and educators awareness of the existence of algorithm bias (Mashburn *et al.*, 2025; Sauder *et al.*, 2024; Scherr *et al.*, 2023; Sharma *et al.*, 2025; Xu *et al.*, 2024), collaboration between stakeholders and end users in model development (Gin *et al.*, 2025; Monzon and Hays, 2025; Spallek *et al.*, 2023), the implementation of monitoring and critical evaluation frameworks by universities (Gin *et al.*, 2025; Robleto *et al.*, 2024; Smirnova *et al.*, 2025; Theros *et al.*, 2025) and the development of context-specific Generative AI (Bray *et al.*, 2025; Cherif *et al.*, 2024; Kıyak and Kononowicz, 2024; Spallek *et al.*, 2023). Addressing the latter strategy, Cherif *et al.* (2024) noted that the prevalence of Western-centric internet may not be representative of slight variations in clinical presentations and disease epidemiology in certain contexts, like African and Asian populations (Cherif *et al.*, 2024).

3.4.1 AI literacy and education. Several studies recommended the critical need to improve AI literacy via education for both students and faculty (Ahmed *et al.*, 2025; Gin *et al.*, 2025; Jagannath *et al.*, 2025; Sunmboye *et al.*, 2025; Theros *et al.*, 2025; Xu *et al.*, 2024). Limited AI literacy was compounded by minimal exposure to AI within existing medical curricula (Jagannath *et al.*, 2025; Ma *et al.*, 2023; Theros *et al.*, 2025). For example, a multi-institutional survey of medical students found that none of the participating universities had a formal AI education program (Jebreen *et al.*, 2024). Another study found regional disparities, with students in lower resource settings less likely to have undertaken AI-related coursework, prompting authors to recommend a national initiative in AI curriculum design (Ma *et al.*, 2023). Prior exposure to AI education appeared to have a protective effect against AI shortcomings, with these students more likely to critically review and verify AI-generated information (Xu *et al.*, 2024).

Recommendations for integrating AI into curricula emphasised the importance of context-specific approaches that reflect population-specific AI usage (Abouammoh *et al.*, 2025; Bray *et al.*, 2025; Mashburn *et al.*, 2025; Mondal, 2025). In low-resource settings, it was noted that, additional resources and infrastructure are required to support this (Ahmed *et al.*, 2025; Jebreen *et al.*, 2024). The breadth of AI literacy recommended to address equity concerns ranges from awareness of how LLMs generate information to the need to develop and teach skills such as computer coding (Ahmed *et al.*, 2025; Gin *et al.*, 2025).

In addition to curriculum design, studies also recommended that university AI policies include equity guidelines (Monzon and Hays, 2025; Rueff *et al.*, 2025). To keep pace with the rapid evolution of AI, Rueff *et al.* (2025) presented a case study of a step-wise process of integrating national AI policy guidelines into the curriculum (Rueff *et al.*, 2025). Faculty AI literacy was identified as critical, with recommendations including faculty supervision of AI models (Robleto *et al.*, 2024) and faculty-led teaching on appropriate AI use (Sauder *et al.*, 2024). Shimuzu *et al.* (2023) proposed a curriculum framework involving collaboration between students and faculty, highlighting the need to learn alongside Generative AI. They suggest that this would require a shift in cognitive domains from "know and understand" to "apply and analyse" (Shimizu *et al.*, 2023).

4. Discussion

The scoping review identified three overarching and intersecting equity themes across the literature: equitable access, bias, and AI literacy and education. Collectively, these findings illustrate a paradox: while AI offers unprecedented potential to democratise access, addressing long-standing barriers that have historically limited inclusivity and equity within medical education, it simultaneously risks reinforcing structural inequities embedded within educational and technological systems. This duality underscores the need for AI literacy and education that is contextual and equity-centred (Varsik and Vosberg, 2024). This pattern reflects the inverse equity hypothesis, whereby newly introduced innovations are initially adopted by wealthier or better-resourced groups, who typically have the least need, before eventually diffusing to more disadvantaged populations (Victora *et al.*, 2000).

Consistent with this pattern, AI was commonly described as a mechanism to enhance access to learning and information across geographic boundaries, yet its benefits were often contingent on resource availability and contextualisation (Ahmed *et al.*, 2025; Biri *et al.*, 2023; Bray *et al.*, 2025; Caudell *et al.*, 2003; Divito *et al.*, 2024; Gin *et al.*, 2025; Jagannath *et al.*, 2025; Jebreen *et al.*, 2024; Kıyak and Kononowicz, 2024; Ma *et al.*, 2023; Mishra *et al.*, 2025; Mondal *et al.*, 2024; Mukadam *et al.*, 2025; Noel, 2024; Pu *et al.*, 2025; Scherr *et al.*, 2023; Spear *et al.*, 2022; Theros *et al.*, 2025; Yli-Hallila *et al.*, 2025). This tension is particularly relevant for LMICs, where pre-existing inequities have been exacerbated by the delayed adoption and more limited integration of AI-enabled medical education compared to high-income countries (Ahsan, 2025; Naseer *et al.*, 2025). In these contexts, limitations in digital infrastructure and local contextualisation are compounded by institutional readiness challenges, alongside the dominance of Western-centric internet resources and English as the de facto language of medicine (Ahsan, 2025; Jagannath *et al.*, 2025). For example, an asynchronous AI course for medical students developed in the USA, with the explicit intention of improving access for learners from LMICs, was instead found to disadvantage non-English speakers, highlighting the potential of an unintended linguistic bias (Jagannath *et al.*, 2025).

Taken together, these factors illustrate how well-intentioned digital education initiatives may inadvertently reproduce or exacerbate existing inequities. Addressing these challenges in LMICs requires not only alternative access models such as partnerships, targeted grants, and sustainable funding arrangements but also deliberate design choices that embed cultural competency and accessibility features from the outset (Jagannath *et al.*, 2025; Kıyak and Kononowicz, 2024). In particular, collaborations between well-resourced and under-resourced institutions offer a pathway to co-develop AI tools that are locally adaptable, affordable, and contextually appropriate for LMIC settings (Kıyak and Kononowicz, 2024; Yli-Hallila *et al.*, 2025). The predominance of studies from high-income countries in this scoping review further highlights the need for expanded research in LMIC contexts to support evidence-informed and contextually appropriate practice.

Moreover, despite the rapid growth of AI in medical education, equity-focused research remains peripheral within the literature. The scoping review confirms that medical education is positioned at a pivotal juncture, shaped by converging imperatives: the pursuit of greater inclusivity and the rapid evolution of AI (Akefe *et al.*, 2025). The momentum of AI in this space is evident in publication trends, with over half (51%) of the included studies published in 2025. Notably, only one study incorporated an equity-related keyword (Monzon and Hays, 2025), and another referenced an equity term in the title (Mishra *et al.*, 2025). Many studies instead examined AI integration more broadly, often referring to “underrepresented” students collectively or listing multiple groups without a focus on any specific equity population (Ahmed *et al.*, 2025; Gin *et al.*, 2025; Meyer *et al.*, 2024). This lack of specificity limits the ability to generate targeted, actionable insights for particular equity populations.

Globally, there is no universal list of equity groups in medical education, as classifications vary by country and context (Jones *et al.*, 2019; Lv *et al.*, 2025). Equity groups of focus in the scoping review included females, CALD populations, students from low socio-economic backgrounds, rural background students, and First Nations students (Ahmed *et al.*, 2025; Biri *et al.*, 2023; Cherif *et al.*, 2024; Jagannath *et al.*, 2025; Jebreen *et al.*, 2024; Kıyak and Kononowicz, 2024; Mashburn *et al.*, 2025; Meyer *et al.*, 2024; Mondal *et al.*, 2024; Rueff *et al.*, 2025; Scherr *et al.*, 2023; Shimizu *et al.*, 2023; Spallek *et al.*, 2023; Sunmboye *et al.*, 2025). Only one paper briefly mentioned students with a disability as an equity group (Robleto *et al.*, 2024), and another explicitly excluded participants unable to use the provided AI hardware due to physical disability (Mukadam *et al.*, 2025). This omission is notable given the potential of AI to support learning for students with disabilities, provided tools are designed for inclusivity (Varsik and Vosberg, 2024; Zhao *et al.*, 2025). Another equity group notably absent from the reviewed literature were LGBTQIA + students, despite their recognition as a priority equity group in national medical education standards (Australian Medical Council, 2023). As with other underrepresented cohorts, LGBTQIA + learners face structural barriers within medical education (Wong *et al.*, 2024). Moreover, heteronormative assumptions are deeply embedded in the language and data used to train AI models, risking the perpetuation of bias and misrepresentation (Wong *et al.*, 2024).

Concerns regarding algorithmic bias were common across studies, with particular emphasis on how LLMs reflect and reinforce the assumptions embedded within their training data. Most AI platforms are trained before public release and do not update continuously, therefore any biases embedded in the training data will persist unless addressed by retraining or fine-tuning (Bhargava and Singhal, 2024; Qiu *et al.*, 2025). At a fundamental level of AI literacy, students and faculty require education on the principles and mechanisms underpinning the development of LLMs (Ahmed *et al.*, 2025; Sauder *et al.*, 2024; Sunmboye *et al.*, 2025).

AI literacy in medical education has been described as minimal, with both students and faculty requiring further support (Jebreen *et al.*, 2024; Theros *et al.*, 2025). Without adequate literacy, there is a risk of overreliance on AI tools and a lack of critical evaluation (Bearman and Ajjawi, 2025; Theros *et al.*, 2025). Given the rapid pace of AI integration, medical schools need to prioritise embedding AI literacy into their curricula to ensure informed and equitable use. A proactive approach is warranted, as accreditation bodies internationally are increasingly recognising digital competence as an essential component of medical education and are likely to formalise such expectations in future standards (Australian Medical Council and Australian Digital Health Agency, 2021; Sapci and Sapci, 2020; Schubert *et al.*, 2025).

Beyond literacy and education, the co-creation of contextually appropriate AI tools with students, faculty and priority equity groups is essential (Kıyak and Kononowicz, 2024; Yli-Hallila *et al.*, 2025). Effective partnerships should encompass data governance, tool development, and ongoing monitoring to ensure inclusion and prevent inequitable outcomes (Jones *et al.*, 2019; Spallek *et al.*, 2023). Further research is needed to obtain contextually translatable evidence on how AI-enabled equitable tools can be co-developed and implemented effectively.

While much of the literature on geographic inequity is focused on LMICs, geographic disparities also persist within high-income countries (Bray *et al.*, 2025; Caudell *et al.*, 2003; Mondal *et al.*, 2024). In this context, AI-enabled distributed learning has been shown to expand access for rural students, enabling them to remain in their communities without compromising educational quality (Bray *et al.*, 2025; Caudell *et al.*, 2003; Mondal *et al.*, 2024; Mukadam *et al.*, 2025). For instance, Bray *et al.* (2025) proposed that AI-powered tools, including virtual patient simulations, personalised learning platforms, clinical decision support systems, and automated performance evaluations, could transform rural medical education by democratising access to resources, standardising learning across regions, and providing tailored learning pathways (Bray *et al.*, 2025).

These innovations are significant given the maldistribution of the medical workforce, which affects countries regardless of income level (World Health Organization, 2021). Rural communities consistently have experienced fewer doctors-to-population ratios compared to metropolitan areas (Fuller *et al.*, 2025; Medical Deans Australia and New Zealand, 2024; World Health Organization, 2021). One key strategy to address this is to provide end-to-end medical training for students from rural backgrounds within their own communities (Fuller *et al.*, 2025). Until recently, structural barriers, such as centralised pre-clinical education in metropolitan centres, have hindered this approach (Fuller *et al.*, 2025; McGrail *et al.*, 2023). In this context, AI-enabled distributed learning offers a potential mechanism to overcome these barriers, supporting more equitable, place-based training models without compromising educational quality.

5. Limitations

As scoping reviews map and collate literature rather than critically appraise study quality, the included studies may have varied in research rigour (Peters *et al.*, 2015). Furthermore, as included studies encompassed a broad range of methodologies, AI modalities, contexts and population groups, the ability to synthesise findings and draw generalisable conclusions may have been compromised. Restricting the search to English-language peer-reviewed literature may have excluded relevant studies in other languages, particularly from non-English speaking LMICs, potentially underrepresenting global perspectives and indicative of the high percentage of studies from high-income countries.

The scoping review relied on pre-defined search terms such as “equity” and “access,” but not all studies that address disparities or inclusivity explicitly used these terms. Consequently, some relevant studies may have been missed, and “access” alone does not necessarily indicate an equity focus. This limitation highlights the challenge of capturing the full breadth of literature on equity in AI-enabled medical education, particularly when terminology is inconsistent or context-specific.

Additionally, the rapid evolution of AI technologies and their integration into medical education means that some included studies may already be outdated, limiting the currency of the review findings. The COVID-19 pandemic also accelerated the adoption of digital and AI-enabled learning, and studies conducted before or during the pandemic may not fully capture post-pandemic educational practices and equity challenges. These factors should be considered when interpreting the generalisability of the findings.

6. Conclusion

AI presents unprecedented opportunities to widen access and participation in medicine for underrepresented groups and standardise medical education globally. Realising these benefits requires AI literacy, contextually relevant tools, and deliberate strategies to mitigate bias.

Medical schools should prioritise embedding AI literacy and education into the curriculum for students and faculty in anticipation of international accreditation standards increasingly mandating AI competence. Future research should focus on developing and evaluating AI interventions that are inclusive, contextually appropriate, and widely accessible.

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Appendix

Table A1. Search strategy used in OVID MEDLINE, Evidenced Based Medicine Reviews–Health Technology Assessment, Health and Psychosocial Instruments and Global Health

#	Search term	Results
1	equit*.mp	73,305
2	access*.mp	888,789
3	“artificial intelligence”.mp	107,190
4	AI.mp	84,371
5	“medical education”.mp	72,466
6	1 or 2	936,486
7	3 or 4	152,797
8	“medical teaching”.mp	1,658
9	“training doctors”.mp	224
10	5 or 8 or 9	74,013
11	6 and 7 and 10	256
12	“training of doctors”.mp	960
13	5 or 8 or 9 or 12	74,664
14	6 and 7 and 13	256

Note(s): All terms were searched using the *.mp.* Field (title, abstract, keyword, and subject heading)

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