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Ethics Education for AI-Mediated Care: A Scoping Review of Curricula, Competencies, Assessment, and Clinical Transfer

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Abstract

Artificial intelligence is entering clinical decision-making faster than health-professions education has established shared expectations for the ethical capabilities clinicians need when using, questioning, explaining, or overriding AI-supported recommendations. Existing literature spans technical literacy, professionalism, ethics teaching, learner attitudes, competency frameworks, assessment, and implementation, but these domains should not be treated as equivalent evidence of clinical competence. This scoping review used PRISMA-ScR-compatible evidence-mapping logic to examine peer-reviewed literature published from 2017 through 2026 on AI-related curricula, competencies, teaching and learning methods, assessment, and transfer relevant to health-professions practice. The auditable selection ledger began with 56 unique candidate publications. All 56 proceeded to documented eligibility assessment; 18 were excluded, leaving 38 publications retained in the manuscript. Of these, 26 constituted the substantive educational evidence map and 12 served methodological, reporting, or contextual functions. Charting distinguished learner group, profession, curriculum focus, pedagogy, assessment construct, outcome level, contextual boundary, and evidential distance from clinical practice. The substantive evidence indicates movement from general AI awareness toward competency-oriented and ethics-explicit education. Recurrent emphases include understanding limitations, critical appraisal, bias and fairness, privacy, transparency, accountability, communication, professional oversight, and responsible use. Teaching ranges from web-based and didactic formats to case-based, problem-based, chatbot-supported, and simulation-oriented learning. Assessment is uneven: self-reported readiness and attitudes are easier to measure than observable ethical performance, and evidence of sustained workplace transfer remains comparatively sparse. Ethics education for AI-mediated care should be distinguished from generic AI literacy and from ethical governance of AI used in education. The review supports a proposed progression from curricular intent through learning and assessment toward near transfer and clinical transfer, while emphasizing that these evidential stages are not interchangeable or causally validated.

Keywords: Artificial intelligence, Medical education, Ethics education, Clinical ethics, Competency assessment, Clinical transfer

Introduction

Artificial intelligence is increasingly embedded in the informational environment of clinical care, while education about its use has developed unevenly. A broad review of AI in medical education documented rapid growth alongside substantial heterogeneity in curricular content, educational purpose, and evaluation [1]. This heterogeneity matters ethically because familiarity with an AI tool is not equivalent to being able to recognize bias, communicate uncertainty, protect patient interests, or contest an inappropriate recommendation.

The ethics-specific educational literature has been narrower. A scoping review devoted to teaching AI ethics in medical education identified a comparatively limited

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and inconsistently operationalized body of work [2]. That gap creates a risk of treating ethical competence as an assumed by-product of technical instruction rather than an educational target requiring its own learning opportunities and assessment evidence.

Recent international digital-health competency work further suggests that safe practice requires capabilities beyond technical literacy, including professional, ethical, and communicative competence [3]. This review maps what ethical capacities are specified, how they are taught and assessed, and whether evidence extends into clinical practice.

Review objectives and questions

A scoping review is appropriate when the purpose is to map concepts, evidence types, and gaps across a heterogeneous field [4]. The objective was therefore to characterize the educational architecture of ethics preparation for AI-mediated care rather than calculate a pooled intervention effect. This choice is consistent with guidance distinguishing broad scoping questions from narrower effectiveness questions suited to other systematic-review designs [5].

The review asked five linked questions. First, what curricula or educational programs address ethical dimensions of clinical AI use? Second, what competencies are specified and how are they defined? Third, what teaching and learning methods are used to develop those competencies? Fourth, what assessment strategies are used, and what claims about competence do those assessments legitimately permit? Fifth, what evidence examines transfer from educational performance to clinical reasoning, workplace behavior, or patient-relevant practice?

These questions separate exposure, learning, assessment, near transfer, and clinical transfer while preserving professional, educational-stage, jurisdictional, technological, and organizational boundaries. Any cross-source framework is presented as a proposed review-derived organizing account, not a validated universal standard.

Protocol and reporting framework

Reporting was structured to be compatible with the PRISMA extension for scoping reviews [6]. Conduct followed updated JBI guidance, including alignment among the review question, eligibility decisions, evidence selection, charting, analysis, and presentation [7]. The review was designed as an evidence map rather than a pooled effectiveness analysis.

Objectives, eligibility boundaries, charting fields, and synthesis categories were treated as protocol-level decisions, consistent with best-practice guidance for scoping-review protocols [8]. Methodological and reporting publications were retained when needed to justify conduct, but they were analytically separated from the substantive educational evidence map. The review therefore distinguishes publications retained for methodological or contextual support from publications contributing evidence about curricula, competencies, teaching, assessment, or transfer.

Eligibility criteria

Eligibility was operationalized around participants, concept, context, publication characteristics, and review purpose, consistent with practical guidance for scoping-review conduct [9]. Substantive sources were eligible when they addressed health-professions learners, educators, clinicians, or professional settings and examined AI-related curriculum, ethical or professional competencies, teaching methods, assessment, or practice-relevant transfer. Medicine, nursing, medical imaging, dentistry, veterinary education, and broader health-professions sources were retained only when their contribution could be bounded to the population and setting actually studied.

Eligible publications were peer-reviewed journal articles published from 2017 through 2026 with a verifiable DOI and a direct role in an exact review domain. Purely technical AI training without an educational or professional-use implication, duplicate versions, non-peer-reviewed material, and sources requiring claims beyond their design, population, profession, jurisdiction, AI modality, or outcome were excluded. Ambiguous cases were resolved against prespecified boundaries rather than topical convenience, reflecting recognized quality challenges in scoping reviews [10].

The operational boundaries and their consequences for subsequent charting are summarized in **Table 1**.

Table 1. Operational eligibility boundaries and downstream charting implications

Review dimension	Inclusion boundary	Exclusion boundary	Downstream charting implication

Learners and professional units	Health-professions students, trainees, educators, clinicians, or profession-specific educational settings	Populations without a defensible health-professions education or clinical-use connection	Preserve profession, learner stage, and role rather than pooling them by default
Educational concept	AI curriculum, ethics or professional competence, teaching, assessment, or practice-relevant transfer	Technical descriptions without an educational or professional-use question	Code the educational claim separately from the technology described
Evidence context	Classroom, online, simulation, curricular, faculty, workplace, or clinical contexts	Contexts requiring unsupported transfer to health care	Record setting and evidential distance between assessed task and clinical practice
Publication status	Peer-reviewed journal article, 2017–2026, verifiable DOI	Preprint, conference-only item, report, website, duplicate version, or out-of-window publication	Maintain a traceable bibliographic record and avoid version duplication
Interpretive boundary	Claim matches the source design, population, context, and outcome	Inclusion would require unsupported causal, universal, patient-level, or clinical-effectiveness inference	Chart both the claim permitted and the claim the evidence cannot support

Note: The table represents the review's operational methodological architecture rather than an empirical finding. Methodological and reporting publications were not counted as substantive educational evidence unless they directly contributed to a mapped educational domain.

Information sources and search strategy

Search reporting followed the principle that information sources, search concepts, dates, and supplementary methods should be reproducible [11]. The search architecture combined terms for artificial intelligence, machine learning, algorithmic systems, generative AI, and clinical decision support with terms for medicine and health professions, education and curriculum, ethics and professionalism, competencies and literacy, teaching, assessment, and transfer.

A directly relevant scoping-review protocol on teaching AI ethics in medical schools reinforced the need for sensitivity to both ethical and technical curricular vocabularies rather than assuming that ethics-focused publications use a single descriptor [12]. Search concepts therefore extended to bias, fairness, privacy, transparency, accountability, explainability, autonomy, responsibility, human oversight, communication, professional judgment, and related constructs.

The surviving auditable record preserved a structured candidate-publication ledger rather than complete raw platform hit counts. Accordingly, the quantitative selection report begins at the point at which unique candidate publications entered the documented screening ledger. Upstream raw search-engine or platform result totals are not retrospectively reconstructed. This limitation is stated explicitly so that the reported PRISMA-ScR flow reflects auditable counts rather than invented database totals.

Evidence selection

Selection reporting followed PRISMA principles distinguishing screening, retrieval, eligibility assessment, exclusion, and inclusion [13]. The auditable ledger contained 56 unique candidate publications after preliminary discovery and bibliographic consolidation. No duplicate DOI remained within this ledger. No retrieval loss is recorded, and all 56 candidate publications proceeded to detailed eligibility assessment. Contemporary scoping-review guidance supports linking selection decisions to predefined eligibility criteria rather than allowing the evidence base to expand through post hoc thematic interest [14]. All 56 candidate publications proceeded to detailed eligibility assessment because the ledger itself represented a topic-focused candidate pool. Eighteen publications were excluded. Eleven were redundant, superseded, or displaced by stronger and more recent sources serving the same review function; three were insufficiently direct in scope for the planned educational claims; and four failed or had unstable bibliographic or Q1-verification eligibility at the audit point.

This left 38 publications retained in the manuscript. Of these, 26 contributed to the substantive educational evidence map, whereas 12 were retained for methodological, reporting, search-design, or contextual purposes and were not treated as included educational studies.

Data charting and coding

Data charting was organized to answer the review questions rather than merely summarize publications. Scoping-review guidance recommends explicit extraction fields, piloting, and alignment between charted information and intended analysis [15]. For each substantive source, charting distinguished article type and design; country or jurisdiction; population or unit; profession and educational stage; data source; focal AI or ethics construct; stated definition or operationalization; teaching mechanism; assessment strategy; outcome; level of analysis; limitation; and transferability boundary. Directly relevant reviews of AI curriculum frameworks show why these distinctions are necessary: educational programs differ by learner stage, curriculum content, delivery format, and evaluation approach [16]. Charting additionally distinguished knowledge, attitudes, self-reported readiness, case-based ethical reasoning, simulated observable performance, workplace behavior, and patient- or process-relevant outcomes.

Missing characteristics were recorded as not reported rather than inferred. Coding separated source-defined categories from categories introduced through review-level interpretation. Any integrated competency taxonomy or relationship among curriculum, assessment, and transfer developed later in the manuscript is therefore identified as a proposed synthesis unless the underlying literature directly establishes it.

Synthesis approach

The synthesis used descriptive evidence mapping and structured narrative comparison rather than meta-analysis. Evidence was organized across curricular characteristics, AI-ethics competencies, teaching and learning methods, assessment strategies, clinical transfer, and evidence gaps. Cross-source synthesis was undertaken only where constructs were sufficiently comparable; otherwise, differences in population, professional role, educational stage, setting, jurisdiction, and AI modality were retained as analytic boundaries.

Profession-specific evidence was not collapsed automatically. A nursing-education scoping review demonstrates that AI applications, educational needs, and reported outcomes arise within profession-specific educational contexts [17]. Similar caution applies to medical imaging, where available AI educational programs reflect distinctive technologies and workflows [18]. Such evidence can inform broader interpretation without justifying unqualified transfer across professions.

The synthesis therefore uses a graded interpretive vocabulary. Source-reported findings are distinguished from cross-source patterns, and cross-source patterns from proposed organizing concepts. Educational exposure, measured learning, case-based reasoning, simulated application, and clinical transfer are treated as different evidential levels. Absence of workplace or patient-level outcomes is interpreted as absence of demonstrated transfer, not evidence that transfer cannot occur.

Evidence-selection results

The auditable selection pathway is numerically reportable from the candidate-ledger stage onward. Fifty-six unique candidate publications entered the documented screening ledger; no duplicate DOI remained in that ledger, and no retrieval loss was recorded. All 56 publications proceeded to detailed eligibility assessment.

Eighteen publications were excluded: 11 because they were redundant or superseded by stronger or more recent sources serving the same evidential function, 3 because their scope was insufficiently direct for the review domains, and 4 because bibliographic or Q1-verification eligibility was insufficient or unstable at the audit point. The reason-specific exclusions therefore reconcile exactly to the full exclusion count would be 18.

Thirty-eight publications were retained. The retained set was then classified by analytic role. Twenty-six publications formed the substantive scoping-review evidence map of curricula, competencies, learner experience, teaching, assessment, and transfer. Twelve publications supported scoping methodology, reporting, search design, or contextual interpretation and were not counted as substantive included educational evidence. This distinction prevents methodological citations from artificially inflating the educational evidence corpus.

Among the retained educational sources, an implemented web-based curriculum for fourth-year medical students provided learner-level evaluation while remaining short of clinical transfer evidence [19]. An applied AI educational program likewise demonstrated assessment of knowledge and application without establishing ethically consequential workplace behavior [20].

Figure 1 reports the reconciled flow and makes explicit that upstream raw search-hit totals were not reconstructed.

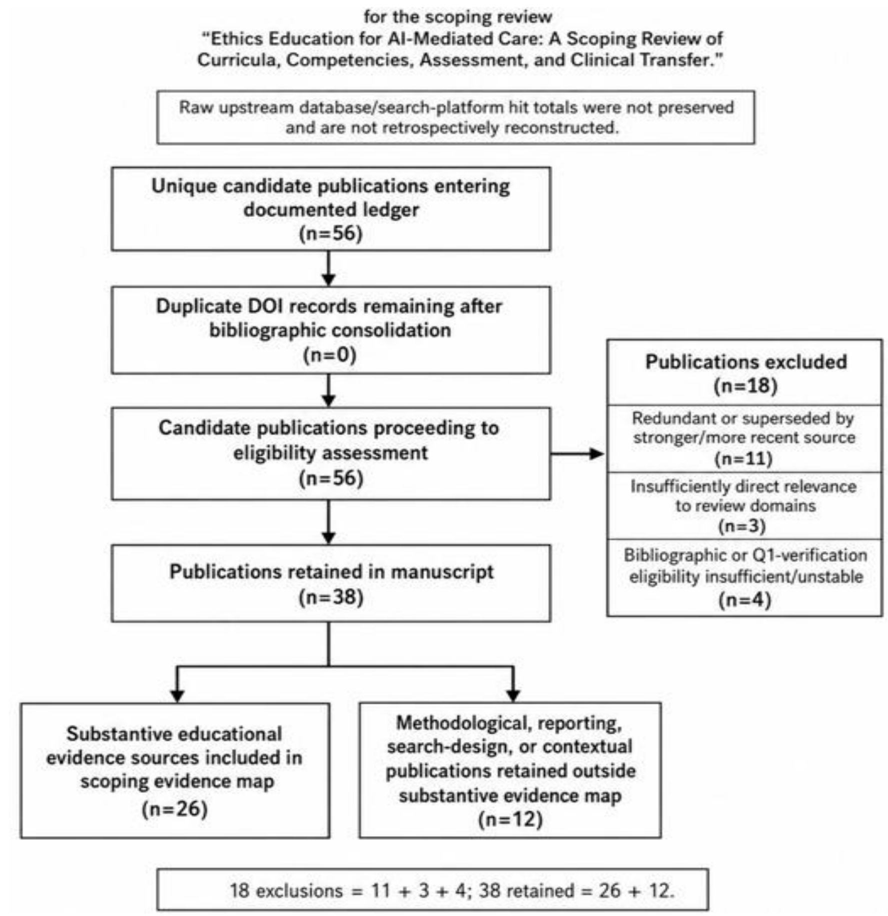

Figure 1. PRISMA-ScR-compatible evidence-selection flow from the auditable candidate ledger

Characteristics of included curricula and publications

The substantive evidence was heterogeneous in profession, learner stage, educational maturity, and intended outcome. Some publications described formal curricula or implemented teaching, whereas others characterized learner exposure, perceived preparedness, or curricular demand. A cross-sectional study of medical students distinguished actual educational exposure from attitudes toward AI and ethical concerns, illustrating why perceived need should not be treated as demonstrated competence [21].

A larger international survey across medical, dental, and veterinary faculties showed that AI exposure and perceived preparedness vary by professional and institutional context [22]. Medicine dominated much of the evidence, but nursing, medical imaging, and other health-professions sources broadened the map and highlighted profession-specific requirements.

The literature also differed in what counted as an outcome. Curriculum descriptions, self-reported confidence, knowledge change, readiness, ethical awareness, contextual reasoning, and workplace needs represent distinct evidential objects. **Table 2** summarizes the characteristics that most directly shaped interpretation.

Table 2. Characteristics of the educational evidence relevant to ethics preparation for AI-mediated care

Evidence form	Typical contribution	What it can establish	Principal interpretive boundary
Implemented curriculum evaluation	Teaching content, delivery, learner engagement, and measured educational outcomes [19]	Feasibility and learner-level change	Does not establish workplace behavior or patient benefit
Applied AI learning program	Connects AI concepts with clinically oriented application [20]	Knowledge or application-oriented learning	Educational application is not equivalent to routine-practice transfer

Learner survey	Maps exposure, perceived need, attitudes, and ethical concerns [21]	Learner perceptions and reported experience	Self-report does not establish competence
Cross-professional survey	Compares preparedness and educational exposure across settings [22]	Contextual and professional variation	Voluntary survey findings may not represent all institutions
Profession-specific synthesis	Preserves nursing, imaging, or other professional contexts	Breadth, recurring themes, and profession-specific gaps	Findings should not be generalized automatically across professions

Note: Categories summarize evidence functions represented in the review and do not constitute a hierarchy of methodological quality.

AI-ethics competencies

Competency-oriented literature moves the field beyond whether learners should simply know about AI. A framework for health professionals identifies capabilities related to evaluating AI tools, recognizing limitations, using them appropriately, and integrating ethical and professional responsibilities into clinical use [23]. These capabilities imply that ethical preparation concerns judgment about when AI output deserves reliance, questioning, explanation, escalation, or rejection.

A Canadian Delphi curriculum-development study likewise integrated foundational and clinical AI knowledge with ethical and professional considerations [24]. Across these sources, the review supports a proposed distinction between AI knowledge and ethical competence for AI-mediated care. The latter requires not only understanding systems but responding appropriately when algorithmic output creates uncertainty, unfairness, opacity, privacy concerns, responsibility conflicts, or tension with patient preferences.

Six recurring competency functions were distinguishable: critical appraisal and limitation recognition; bias and fairness recognition; privacy and data responsibility; transparency and communication; responsibility and oversight; and context-sensitive professional judgment. This six-part organization is proposed here as a review-derived mapping device, not as a validated competency standard.

Table 3 maps these functions to assessable educational claims.

Table 3. Proposed mapping of AI-ethics competency functions and assessable educational claims

Proposed competency function	Educational focus	Stronger evidence would require	Claim that should not be inferred
Critical appraisal and limitation recognition	Identify uncertainty, failure conditions, and inappropriate reliance	Case or performance tasks requiring justified acceptance or rejection	Technical knowledge alone proves safe AI use
Bias and fairness recognition	Detect differential performance or distributive concerns	Contextual cases involving affected populations and competing fairness considerations	Awareness of bias demonstrates equitable practice
Privacy and data responsibility	Recognize confidentiality, governance, and data-use obligations	Applied tasks requiring defensible handling of data-related dilemmas	Recalling privacy principles proves compliant behavior
Transparency and communication	Explain AI involvement, uncertainty, and limitations in clinically meaningful terms	Observed patient-facing or simulated communication	Confidence in explanation equals communication competence
Responsibility and oversight	Identify when human review, escalation, or accountability is required	Performance tasks involving responsibility conflicts and override decisions	Human presence alone guarantees meaningful oversight
Context-sensitive professional judgment	Integrate AI output with patient values, clinical context, and professional reasoning	Longitudinal or workplace assessment of justified decisions	A correct classroom answer proves clinical transfer

Note: The competency functions are an original proposed synthesis derived from recurring domains in the reviewed competency literature and require validation.

Teaching and learning methods

Teaching approaches ranged from structured curricular modules to active, case-based, problem-based, conversational, and simulation-oriented learning. Direct ethics-focused intervention evidence remains comparatively uncommon. A quasi-experimental study of nursing students evaluated an AI-focused ethics education program using ethical awareness, moral sensitivity, attitudes, and intended generative-AI adoption as learner-level outcomes [25]. These measures show that explicit ethics teaching can be evaluated, while the design and outcome level do not establish sustained clinical behavior.

More interactive approaches attempt to move learners from declarative knowledge toward situated use. Work involving ChatGPT, chatbot development, and simulation-based learning illustrates how AI literacy can be developed through tasks requiring learners to engage with systems rather than receive information passively [26]. For ethics education, the pedagogical implication is not that simulation is inherently superior, but that competencies involving judgment, explanation, uncertainty, and oversight require opportunities to practice those actions.

Pedagogy should therefore match the intended claim. Didactic formats may support conceptual knowledge; cases can expose conflicts and trade-offs; simulation can support observable performance; and workplace learning becomes necessary when the intended outcome is actual clinical transfer.

Assessment strategies

Assessment was one of the clearest points at which conceptual imprecision could generate overclaiming. The Medical Artificial Intelligence Readiness Scale for Medical Students provides psychometric evidence for measuring self-reported AI readiness [27]. Such instruments can be useful for educational planning and learner self-perception, but readiness scores should not be interpreted as direct evidence that a learner can manage an ethically difficult AI-mediated clinical decision.

Contemporary health-professions assessment guidance emphasizes construct clarity, defensible interpretation, and attention to how AI changes both assessment processes and what counts as credible evidence of competence [28]. For AI ethics, assessment therefore needs to specify whether it measures knowledge, attitudes, reasoning, observable performance, or behavior.

The review supports a proposed assessment-distance principle: the further an educational claim moves from knowing ethical concepts toward performing ethically in real clinical environments, the closer the assessment should approximate the conditions under which that claim is expected to hold. This is an interpretive synthesis, not an empirically validated rule. It discourages treating self-reported confidence as competence or a single educational exercise as proof of durable clinical behavior.

Evidence of clinical transfer

Evidence becomes much thinner when the outcome shifts from learning to practice. A mixed-methods study of problem-based AI-ethics education among Japanese medical students examined changes in knowledge and contextual ethical reasoning [29]. Such findings matter because contextualized cases are closer to applied judgment than decontextualized recall; nevertheless, they remain near-transfer evidence within an educational environment rather than observation of clinicians managing AI-supported decisions in routine care.

Workplace-focused qualitative evidence provides a different perspective. A Flanders case study of health-care AI literacy identified practical needs, organizational conditions, and implementation barriers affecting professionals' ability to use AI meaningfully in practice [30]. Such evidence describes conditions relevant to transfer but does not demonstrate that a particular curriculum caused workplace competence.

Table 4 separates educational activity from assessment level and the transfer claim legitimately supported.

Table 4. Teaching, assessment, and the evidential distance to clinical transfer

Educational or evidence form	Typical assessment object	Evidential level	Transfer claim permitted
Structured AI-ethics teaching [25]	Ethical awareness, sensitivity, attitudes, intentions	Learner-level educational outcome	Teaching can influence measured educational constructs
Interactive or simulation-oriented AI learning [26]	Task engagement, knowledge, applied learning	Applied educational performance	Learners can practice context-relevant AI use
Readiness measurement [27]	Self-reported preparedness	Perception/readiness	Perceived readiness can be quantified
Case- or problem-based ethics learning [29]	Contextual reasoning in educational cases	Near transfer	Learners may apply ethical concepts to simulated or case contexts

Workplace AI-literacy inquiry [30]	Practice needs, barriers, organizational conditions	Clinical-context evidence	Conditions affecting real-world use can be identified

Note: No row demonstrates patient-level benefit or durable clinical behavior unless those outcomes are directly observed.

Curriculum and evidence gaps

Recent undergraduate mapping confirms that AI education is expanding, but implementation, curricular standardization, and evaluation remain uneven [31]. The central gap is therefore not simply absence of content. It is weak alignment among the ethical capability a curriculum claims to develop, the learning opportunity provided, the assessment evidence collected, and the level of transfer subsequently inferred.

Ethical implementation guidance further shows that privacy, bias, transparency, integrity, and responsibility remain active concerns when AI enters medical education [32]. These issues have two meanings that should not be conflated: learners may need education about the ethics of clinical AI, while institutions also face ethical obligations when using AI as an educational technology.

Across the reviewed evidence, the sparsest zone is the transition from assessed educational reasoning to observed clinical performance. There is also limited evidence concerning durability, multidisciplinary team use, patient communication, equity-sensitive performance, and organizational conditions supporting appropriate override or escalation.

Figure 2 maps this evidential landscape without assigning numerical scores or causal meaning.

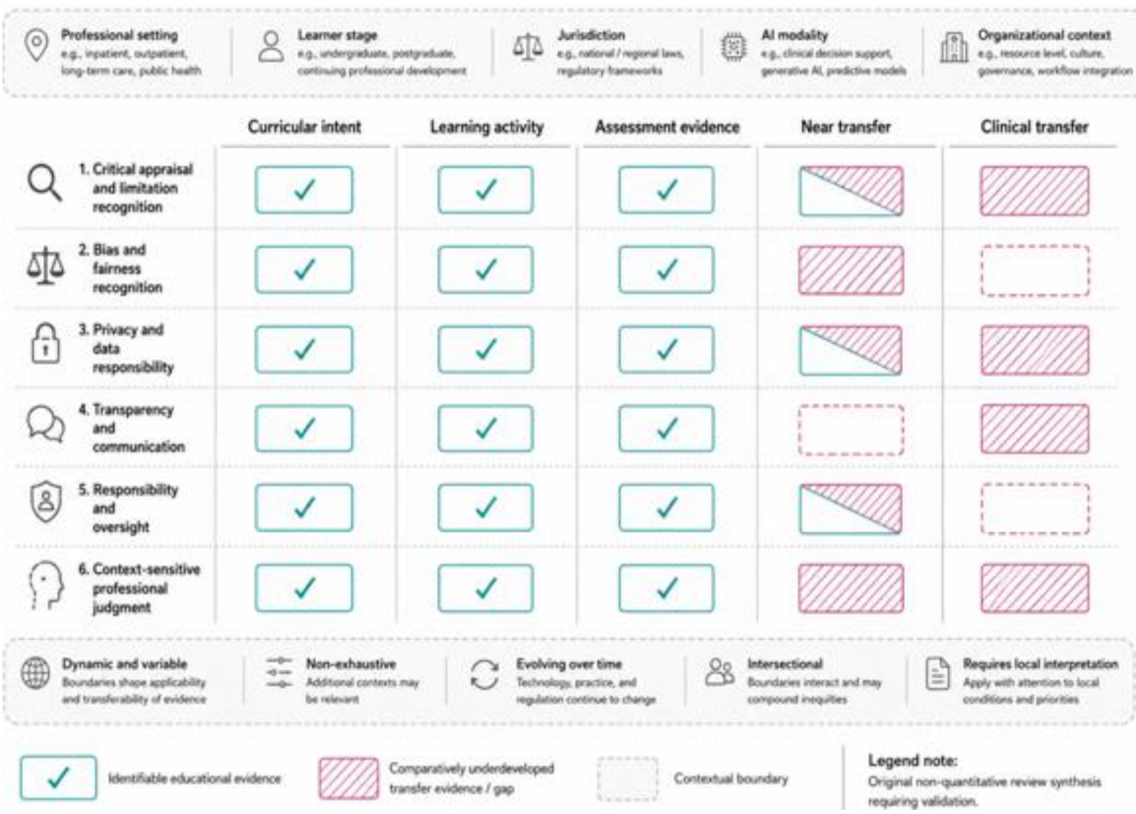

Figure 2. Multidimensional evidence map from AI-ethics curriculum to clinical transfer

Discussion

The literature has progressed beyond asking whether health professionals should learn about AI. Contemporary competency work increasingly specifies what learners should understand and do, while recent framework development also acknowledges the need for longer-term practice evaluation [33]. The consequential distinction is between curricular presence and ethically defensible performance. A curriculum can contain ethics content without demonstrating that learners can recognize an AI-related moral problem, reason through it, communicate uncertainty, or act appropriately when patient interests and algorithmic recommendations diverge.

A second distinction concerns ethics about AI-mediated care versus ethics of using AI within education. A recent scoping review of ethical considerations in AI-supported medical education demonstrates that these domains overlap but are not interchangeable [34]. Governance of educational AI does not substitute for teaching clinicians how to respond ethically to clinical AI.

Across broad curriculum reviews, heterogeneity and incomplete standardization remain recurrent field-level findings [1, 16, 31]. The synthesis developed here therefore proposes an alignment problem rather than merely a content deficit: competency claims, pedagogical opportunities, assessment tasks, and transfer claims should be examined as linked but non-equivalent evidential stages. That proposition is suitable for prospective testing; it is not established as a causal educational model.

Agenda for curriculum development

Future curriculum development should begin with explicit claims about the capability being sought. A systematic review of AI skills for future health professionals shows recurring skill domains but also a limited and uneven evidence base from which priorities are being inferred [35]. Curriculum designers should distinguish widely recurring competencies from locally important additions and from capabilities for which empirical assessment remains immature.

Implementation guidance favors progressive, integrated, context-sensitive curriculum development rather than isolated exposure to AI topics [36]. For ethics education, progression should mean increasing task authenticity: conceptual foundations can precede structured cases; cases can precede observed simulation; and real-practice assessment should be considered when programs claim workplace competence.

Recent competency sources converge on combining technical literacy with clinically situated ethical and professional judgment [23, 24, 35]. Research should now test whether that integration produces defensible performance. Priority designs include longitudinal multisite studies, validated case and simulation assessments, workplace-based observation, implementation-fidelity analysis, equity-sensitive subgroup analysis, and, where appropriate, patient- or process-relevant outcomes. Comparative trials may be informative, but no single design is sufficient for every competency or transfer question.

Limitations

The evidence spans professions, educational stages, countries, AI modalities, and outcomes. Nursing evidence, for example, has its own educational and practice context and should not be transferred unqualified to all health professions [37]. Review-of-review overlap also requires caution when interpreting thematic convergence.

The field is changing rapidly. A recent scoping review of generative AI in health-professions teaching and assessment illustrates how quickly educational uses, integrity concerns, and reliability questions are evolving [38]. Conclusions are therefore time-bounded and may not transfer equally across generative systems, predictive models, imaging algorithms, or decision-support tools. The PRISMA-ScR flow is fully numeric from the auditable candidate-ledger stage, but raw upstream platform-hit totals were not preserved and are not reconstructed.

Conclusion

Ethics education for AI-mediated care is developing from general awareness toward explicit competencies, pedagogies, and assessments, but evidence becomes progressively weaker as claims approach real clinical performance. This review proposes an alignment framework linking competency definition, learning opportunity, assessment evidence, near transfer, and clinical transfer while keeping these stages analytically distinct. Self-reported readiness should not be treated as competence, educational performance should not automatically be treated as workplace transfer, and ethics education should not be reduced to technical AI literacy. Future work should test context-sensitive ethical performance across professions, institutions, AI modalities, and patient-care settings before universal curricular or implementation claims are made.

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References

1. Gordon M, Daniel M, Ajiboye A, Uraiby H, Xu NY, Bartlett R, et al. A scoping review of artificial intelligence in medical education: BEME Guide No. 84. Med Teach. 2024;46(4):446-70. doi:10.1080/0142159X.2024.2314198
2. Weidener L, Fischer M. Teaching AI ethics in medical education: A scoping review of current literature and practices. Perspect Med Educ. 2023;12(1):399-410. doi:10.5334/pme.954
3. Car J, Ong QC, Erlikh Fox T, Leightley D, Kemp SJ, Švab I, et al. The Digital Health Competencies in Medical Education Framework: An international consensus statement based on a Delphi study. JAMA Netw Open. 2025;8(1):e2453131. doi:10.1001/jamanetworkopen.2024.53131
4. Munn Z, Pollock D, Khalil H, Alexander L, McInerney P, Godfrey CM, et al. What are scoping reviews? Providing a formal definition of scoping reviews as a type of evidence synthesis. JBI Evid Synth. 2022;20(4):950-2. doi:10.11124/JBIES-21-00483
5. Munn Z, Peters MDJ, Stern C, Tufanaru C, McArthur A, Aromataris E. Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. BMC Med Res Methodol. 2018;18(1):143. doi:10.1186/s12874-018-0611-x
6. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and explanation. Ann Intern Med. 2018;169(7):467-73. doi:10.7326/M18-0850
7. Peters MDJ, Marnie C, Tricco AC, Pollock D, Munn Z, Alexander L, et al. Updated methodological guidance for the conduct of scoping reviews. JBI Evid Synth. 2020;18(10):2119-26. doi:10.11124/JBIES-20-00167
8. Peters MDJ, Godfrey C, McInerney P, Khalil H, Larsen P, Marnie C, et al. Best practice guidance and reporting items for the development of scoping review protocols. JBI Evid Synth. 2022;20(4):953-68. doi:10.11124/JBIES-21-00242
9. Pollock D, Davies EL, Peters MDJ, Tricco AC, Alexander L, McInerney P, et al. Undertaking a scoping review: A practical guide for nursing and midwifery students, clinicians, researchers, and academics. J Adv Nurs. 2021;77(4):2102-13. doi:10.1111/jan.14743
10. Khalil H, Peters MDJ, Tricco AC, Pollock D, Alexander L, McInerney P, et al. Conducting high quality scoping reviews-challenges and solutions. J Clin Epidemiol. 2021;130:156-60. doi:10.1016/j.jclinepi.2020.10.009
11. Rethlefsen ML, Kirtley S, Waffenschmidt S, Ayala AP, Moher D, Page MJ, et al. PRISMA-S: An extension to the PRISMA statement for reporting literature searches in systematic reviews. J Med Libr Assoc. 2021;109(2):174-200. doi:10.5195/jmla.2021.962
12. Bardakçı T, Barış M, Dabbagh H, Savulescu J, Saraçoğlu M, Razai MS. Teaching AI ethics in medical schools: A scoping review protocol on the ethical-technical balance in curricular frameworks. BMJ Open. 2026;16(6):e111721. doi:10.1136/bmjopen-2025-111721
13. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ. 2021;372:n71. doi:10.1136/bmj.n71
14. Pollock D, Evans C, Jia RM, Alexander L, Pieper D, Brandão de Moraes É, et al. “How-to”: Scoping review? J Clin Epidemiol. 2024;176:111572. doi:10.1016/j.jclinepi.2024.111572
15. Pollock D, Peters MDJ, Khalil H, McInerney P, Alexander L, Tricco AC, et al. Recommendations for the extraction, analysis, and presentation of results in scoping reviews. JBI Evid Synth. 2023;21(3):520-32. doi:10.11124/JBIES-22-00123
16. Tolentino R, Baradaran A, Gore G, Pluye P, Abbasgholizadeh-Rahimi S. Curriculum frameworks and educational programs in AI for medical students, residents, and practicing physicians: Scoping review. JMIR Med Educ. 2024;10:e54793. doi:10.2196/54793
17. Lifshits I, Rosenberg D. Artificial intelligence in nursing education: A scoping review. Nurse Educ Pract. 2024;80:104148. doi:10.1016/j.nepr.2024.104148
18. Doherty G, McLaughlin L, Hughes C, McConnell J, Bond R, McFadden S. A scoping review of educational programmes on artificial intelligence (AI) available to medical imaging staff. Radiography (Lond). 2024;30(2):474-82. doi:10.1016/j.radi.2023.12.019

19. Abid A, Murugan A, Banerjee I, Purkayastha S, Trivedi H, Gichoya J. AI education for fourth-year medical students: Two-year experience of a web-based, self-guided curriculum and mixed methods study. JMIR Med Educ. 2024;10:e46500. doi:10.2196/46500
20. Krive J, Isola M, Chang L, Patel T, Anderson M, Sreedhar R. Grounded in reality: Artificial intelligence in medical education. JAMIA Open. 2023;6(2):ooad037. doi:10.1093/jamiaopen/ooad037
21. Weidener L, Fischer M. Artificial intelligence in medicine: Cross-sectional study among medical students on application, education, and ethical aspects. JMIR Med Educ. 2024;10:e51247. doi:10.2196/51247
22. Busch F, Hoffmann L, Truhn D, Ortiz-Prado E, Makowski MR, Bressem KK, et al. Global cross-sectional student survey on AI in medical, dental, and veterinary education and practice at 192 faculties. BMC Med Educ. 2024;24(1):1066. doi:10.1186/s12909-024-06035-4
23. Russell RG, Lovett Novak L, Patel M, Garvey KV, Craig KJT, Jackson GP, et al. Competencies for the use of artificial intelligence-based tools by health care professionals. Acad Med. 2023;98(3):348-56. doi:10.1097/ACM.0000000000004963
24. Singla R, Pupic N, Ghaffarizadeh SA, Kim C, Hu R, Forster BB, et al. Developing a Canadian artificial intelligence medical curriculum using a Delphi study. NPJ Digit Med. 2024;7(1):323. doi:10.1038/s41746-024-01307-1
25. Abuadas M, Albikawi Z, Rayani A. The impact of an AI-focused ethics education program on nursing students' ethical awareness, moral sensitivity, attitudes, and generative AI adoption intention: A quasi-experimental study. BMC Nurs. 2025;24(1):720. doi:10.1186/s12912-025-03458-2
26. Naamati-Schneider L, Alt D. Developing AI literacy in medical and health professions education: Exploring ChatGPT, ChatBots development, and simulation-based learning. Nurse Educ Pract. 2025;88:104572. doi:10.1016/j.nepr.2025.104572
27. Karaca O, Çalışkan SA, Demir K. Medical artificial intelligence readiness scale for medical students (MAIRS-MS): Development, validity and reliability study. BMC Med Educ. 2021;21(1):112. doi:10.1186/s12909-021-02546-6
28. Masters K, MacNeil H, Benjamin J, Carver T, Nemethy K, Valanci-Aroesty S, et al. Artificial intelligence in health professions education assessment: AMEE Guide No. 178. Med Teach. 2025;47(9):1410-24. doi:10.1080/0142159X.2024.2445037
29. Ota Y, Asada Y, Kubo S, Kanno T, Saeki Yagi M, Matsuyama Y. Evaluation of a problem-based learning program's effect on artificial intelligence ethics among Japanese medical students: Mixed methods study. JMIR Med Educ. 2026;12:e84535. doi:10.2196/84535
30. Chatzichristos C, Chatzichristos G, Borremans I, Gruyaert S, De Vos I, De Vos M, et al. Bridging the AI-literacy gap in health care: Qualitative analysis of the Flanders case study. J Med Internet Res. 2025;27:e76709. doi:10.2196/76709
31. Simoni J, Urtubia-Fernandez J, Mengual E, Simoni DA, Royo M, Egaña-Yin D, et al. Artificial intelligence in undergraduate medical education: An updated scoping review. BMC Med Educ. 2025;25(1):1609. doi:10.1186/s12909-025-08188-2
32. Franco D'Souza R, Mathew M, Mishra V, Surapaneni KM. Twelve tips for addressing ethical concerns in the implementation of artificial intelligence in medical education. Med Educ Online. 2024;29(1):2330250. doi:10.1080/10872981.2024.2330250
33. Cai C, Zhu G, Zhou SM, Ng O, Duell J, Ho WK, et al. A competency framework for medical AI education: Mixed methods study. JMIR Med Educ. 2026;12:e91116. doi:10.2196/91116
34. Itani A, Gronseth SL, Musaad S, Nguyen T, Mirabile Y, Beech BM. Ethical considerations for teaching with artificial intelligence: A scoping review in medical education settings. Int J Educ Technol High Educ. 2025;22(1):68. doi:10.1186/s41239-025-00563-9
35. Gazquez-Garcia J, Sánchez-Bocanegra CL, Sevillano JL. AI in the health sector: Systematic review of key skills for future health professionals. JMIR Med Educ. 2025;11:e58161. doi:10.2196/58161
36. Kim DH, Kang YJ, Lee YM. Twelve tips for developing and implementing AI curriculum for undergraduate medical education. Med Educ Online. 2025;30(1):2585637. doi:10.1080/10872981.2025.2585637

37. El Arab RA, Al Moosa OA, Abuadas FH, Somerville J. The role of AI in nursing education and practice: Umbrella review. J Med Internet Res. 2025;27:e69881. doi:10.2196/69881

38. Astbury H, Fortune E, Dal Ponte C, Lyons K, Shaw L. Generative artificial intelligence for teaching and assessment in health professions education: A scoping review. Nurse Educ Pract. 2026;91:104697. doi:10.1016/j.nepr.2025.104697