REFERENCE #	CITATION	EVIDENCE TYPE	SAMPLE SIZE/ POPULATION	INTERVENTION(S)	CONTROL/ COMPARISON	OUTCOME MEASURE(S)	CONCLUSION(S)	CONSENSUS
1	Collins GS, Moons KGM, Dhiman P et al. TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. BMJ. 2024;385:e078378. doi: 10.1136/bmj-2023-078378 [VA]	Consensus	n/a	n/a	n/a	n/a	The TRIPOD reporting guidance was updated to include reporting recommendations for studies of prediction models. This tool can be used by health care professionals to evaluate whether sufficient details about the AI-enabled technology are available before integration into clinical use.	IVB
2	Olczak J, Pavlopoulos J, Prijs J et al. Presenting artificial intelligence, deep learning, and machine learning studies to clinicians and healthcare stakeholders: an introductory reference with a guideline and a Clinical AI Research (CAIR) checklist proposal. Acta Orthop. 2021;92(5):513–525. doi: 10.1080/17453674.2021.1918389 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	AI will be an important clinical tool and clinicians need to be able to understand and interpret research results related to artificial intelligence. The CAIR checklist was developed to facilitate clinician use for interpretation and incorporation of AI-related research.	VA
3	Good Machine Learning Practice for Medical Device Development: Guiding Principles. US Food & Drug Administration. December 19 , 2025. Accessed April 8, 2026. https://www.fda.gov/medical-devices/software-medical-device-samd/good-machine-learning-practice-medical-device-development-guiding-principles [IVB]	Position Statement	n/a	n/a	n/a	n/a	The FDA, Health Canada, and UK MHRA jointly published 10 guiding principles for good machine learning practice, including a multidisciplinary approach, cybersecurity, robust data collection and management, emphasis on human-AI interaction, and monitoring across the AI lifecycle.	IVB
4	Mastrodicasa D, van Assen M, Huisman M et al. Use of AI in cardiac CT and MRI: a scientific statement from the ESCR, EuSoMII, NASCI, SCCT, SCMR, SIIM, and RSNA. Radiology. 2025;314(1):e240516. doi: 10.1148/radiol.240516 [VA]	Position Statement	n/a	n/a	n/a	n/a	AI integration in cardiac CT and MRI holds great potential, but most tools remain in development and substantial effort is required for clinical use. Critical evaluation is essential to ensure tools meet real needs in the cardiac imaging workflow. Bridging innovation and robust, cost-effective, sustainable solutions is imperative for widespread deployment.	IVA
5	ISO/IEC 42001:2023. Information technology — Artificial intelligence — Management system. 1st rd. International Organization for Standardization (ISO); 2023. [IVB]	Guideline	n/a	n/a	n/a	n/a	ISO developed guidelines for a framework for organizations to adopt structures and policies for an AI management system including determining and addressing risks and opportunities.	IVB
6	Tsoi AH, Gartner G, Cotten SW et al. Establishing and implementing a responsible artificial intelligence framework: a 1-year review. J Am Med Inform Assoc. 2025;32(11):1778–1784. doi:10.1093/jamia/ocaf147 [VA]	Organizational Experience	Health system implementing a Responsible AI evaluation framework	n/a	n/a	n/a	The Responsible AI framework uses a 21-question survey on fairness, transparency, accountability, and trustworthiness, applied by an interdisciplinary team. In year one it evaluated 12 AI technologies, but the volunteer-based process proved unsustainable without broader institutional support, revealing a need for better bias mitigation, demographic performance analysis, and shared post-deployment monitoring.	VA
7	Boag W, Hasan A, Kim JY et al. The algorithm journey map: a tangible approach to implementing AI solutions in healthcare. NPJ Digit Med. 2024;7(1):87. doi: 10.1038/s41746-024-01061-4 [VA]	Organizational Experience	n/a	n/a	n/a	Identify and navigate barriers to AI/ML adoption in healthcare settings	One health system's experience developing an AI-based sepsis tool, spanning problem identification, model development, technical and clinical integration, and lifecycle management. Success required extensive interdisciplinary collaboration, iterative refinement, and clearly defined project goals from the outset.	VA
8	Kaduwela NA, Horner S, Dadar P, Manworren RCB. Application of a human-centered design for embedded machine learning model to develop data labeling software with nurses: Human-to-Artificial Intelligence (H2AI). Int J Med Inform. 2024;183:105337. doi: 10.1016/j.ijmedinf.2023.105337 [VA]	Organizational Experience	6 nurses	n/a	n/a	n/a	Nurses' engagement in CDSS development was critical to addressing their priorities, reflecting their decision-making, and earning their trust for adoption. Human-centered design can positively influence involvement, training, competency, resistance to change, and perceptions of AI quality.	VA
9	Beecy AN, Longhurst CA, Singh K, Wachter RM, Murray SG. The chief health AI officer—an emerging role for an emerging technology. NEJM AI. 2024;1(7). doi: 10.1056/AIp2400109 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Establishing a Chief Health AI Officer is a crucial step toward successful AI initiatives spanning data infrastructure, talent development, technology selection, safe practices, and continuous improvement. The role is key to collaboration among IT, clinicians, and AI developers; to building and maintaining robust governance; and to tracking evolving regulatory standards.	VA
10	Position Statement: The Ethical Use of Artificial Intelligence in Nursing Practice. American Nurses Association; 2022. Accessed April 8, 2026. https://www.nursingworld.org/globalassets/practiceandpolicy/nursing-excellence/ana-position-statements/the-ethical-use-of-artificial-intelligence-in-nursing-practice_bod-approved-12_20_22.pdf [IVB]	Position Statement	n/a	n/a	n/a	n/a	The American Nurses Association holds that appropriate use of AI supports nursing's core values and ethical obligations. AI should not replace nursing skill or judgment but should assist and augment practice while preserving caring and compassion.	IVA

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11	Khan SD, Hoodbhoy Z, Raja MHR et al. Frameworks for procurement, integration, monitoring, and evaluation of artificial intelligence tools in clinical settings: a systematic review. PLoS Digit Health. 2024;3(5):e0000514. doi: 10.1371/journal.pdig.0000514 [VA]	Literature Review	n/a	n/a	n/a	n/a	Existing AI implementation frameworks largely focus on the initial stage and are developed with little input from LICs/LMICs. Future adoption requires a more comprehensive, inclusive framework built through global collaboration across socioeconomic contexts, along with additional studies evaluating these parameters.	VA
12	Kim JY, Hasan A, Kellogg KC et al. Development and preliminary testing of Health Equity Across the AI Lifecycle (HEAAL): a framework for healthcare delivery organizations to mitigate the risk of AI solutions worsening health inequities. PLoS Digit Health. 2024;3(5):e0000390. doi: 10.1371/journal.pdig.0000390 [VA]	Consensus	Interviewed 89 individuals from 10 US healthcare delivery organizations	n/a	n/a	n/a	Healthcare leaders find it hard to identify and objectively measure an AI product's potential impact on health inequities. The authors describe 8 key decision points across the AI lifecycle and provide a framework for organizations to integrate AI into the clinical setting.	IVB
13	Daneshjou R, Smith MP, Sun MD, Rotemberg V, Zou J. Lack of transparency and potential bias in artificial intelligence data sets and algorithms: a scoping review. JAMA Dermatol. 2021;157(11):1362–1369. doi: 10.1001/jamadermatol.2021.3129 [VB]	Literature Review	70 unique studies	n/a	n/a	n/a	Three data-set issues should be addressed before clinical translation of AI algorithms for skin disease: sparse data-set characterization and lack of transparency, nonstandard and unverified disease labels, and inability to fully assess patient diversity in development and testing.	VB
14	Elendu C, Amaechi DC, Elendu TC et al. Ethical implications of AI and robotics in healthcare: a review. Medicine (Baltimore). 2023;102(50):e36671. doi: 10.1097/MD.0000000000036671 [VA]	Literature Review	n/a	n/a	n/a	n/a	Integrating AI and robotics into healthcare marks a monumental shift, promising improved diagnostics, treatments, and care delivery, but it brings complex ethical considerations requiring careful navigation. The authors prioritize patient welfare, transparency, fairness, and collaboration, and outline adaptable guidelines with best-practice recommendations.	VA
15	Augmented Intelligence Development, Deployment, and Use in Health Care. American Medical Association; 2024. Accessed April 8, 2026. https://www.ama-assn.org/system/files/ama-ai-principles.pdf [IVB]	Consensus	n/a	n/a	n/a	n/a	Summarizes AMA advocacy principles covering AI oversight, disclosure requirements, liability, data privacy and security, and payor use of AI. Continued gaps in regulatory guidance and transparency mandates leave a critical hole in the oversight of AI-enabled medical devices.	IVA
16	Stogiannos N, Malik R, Kumar A et al. Black box no more: a scoping review of AI governance frameworks to guide procurement and adoption of AI in medical imaging and radiotherapy in the UK. Br J Radiol. 2023;96(1152):20221157. doi: 10.1259/bjr.20221157 [VA]	Literature Review	n/a	n/a	n/a	n/a	Rigorous validation, evaluation, and ongoing monitoring of AI models are necessary to ensure safety and clinical effectiveness. Adoption is facilitated by staff education, multidisciplinary collaboration, and involving patients, the public, and practitioners in decision-making. A comprehensive AI governance framework guided by fairness, transparency, trustworthiness, and explainability is also needed.	VA
17	Price WN, Sendak M, Balu S, Singh K. Enabling collaborative governance of medical AI. Nat Mach Intell. 2023;5(8):821–823. doi: 10.1038/s42256-023-00699-1 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Medical artificial intelligence requires governance, both centrally and locally, to ensure safety and effectiveness, with practical collaborative governance enabling health systems to handle these tasks, supported by central regulators.	VA
18	Lekadir K, Frangi AF, Porras AR et al. FUTURE-AI: international consensus guideline for trustworthy and deployable artificial intelligence in healthcare. BMJ. 2025;388:e081554. doi: 10.1136/bmj-2024-081554 [VA]	Consensus	n/a	n/a	n/a	n/a	A consortium was founded to establish guidelines for the design, development, validation, regulation, deployment and monitoring of AI-enabled technology in health care delivery.	IVA
19	Bach TA, Khan A, Hallock H, Beltrão G, Sousa S. A systematic literature review of user trust in AI-enabled systems: an HCI perspective. Int J Hum Comput Interact. 2024;40(5):1251–1266. doi: 10.1080/10447318.2022.2138826 [IIIA]	Systematic Review	23 articles, 2012-2021	n/a	n/a	n/a	User trust in AI-enabled systems is shaped by socio-ethical considerations, technical and design features, and user characteristics. Trust should be addressed directly in every context of use; it is influenced by user-system interactions and can increase over time.	IIIA
20	Wu C, Xu H, Bai D, Chen X, Gao J, Jiang X. Public perceptions on the application of artificial intelligence in healthcare: a qualitative meta-synthesis. BMJ Open. 2023;13(1):e066322. doi: 10.1136/bmjopen-2022-066322 [IIIA]	Systematic Review w/ Meta-Analysis	n/a	n/a	n/a	n/a	The public recognizes medical AI's distinct advantages and convenience, but concerns—largely ethical and legal—were observed. Standardized application and reasonable oversight are key to effective, safe use. The analysis offers health managers insights and suggestions for implementing medical AI smoothly while ensuring patient safety.	IIIA

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21	Artificial Intelligence Risk Management Framework (AI RMF 1.0). National Institute of Standards and Technology (NIST); 2023. Accessed April 8, 2026. https://tsapps.nist.gov/publication/get_pdf.cfm?pub_id=936225 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	The AI RMF is a living document offering voluntary guidelines for managing AI risks and promoting trustworthy development. It emphasizes human-centricity, social responsibility, and sustainability, and is designed to be adaptable to evolving technologies and standards.	VA
22	Schwartz R, Vassilev A, Greene K, Perine L, Burt A, Hall P. Towards a Standard for Identifying and Managing Bias in Artificial Intelligence. National Institute of Standards and Technology (NIST); 2022. Accessed April 8, 2026. https://tsapps.nist.gov/publication/get_pdf.cfm?pub_id=934464 [VA]	Literature Review	n/a	n/a	n/a	n/a	NIST intends to develop further consensus socio-technical guidance with the research community and a broad set of stakeholders, including those directly impacted by AI bias. The guidance is meant to assist organizations that commission, design, develop, deploy, use, or evaluate AI across varied use cases.	VA
23	Blueprint for Trustworthy AI: Implementation Guidance and Assurance for Healthcare. Version 1.0. Coalition for Health AI (CHAI); 2023. Accessed April 8, 2026. https://chai.org/responsible-ai-guide/ [VA]	Expert Opinion	n/a	n/a	n/a	n/a	AI in healthcare offers enormous potential to accelerate clinical research and improve care quality and efficiency. However, it may also increase risks of negative patient outcomes and introduce or worsen bias. An urgent need exists for a framework centered on health impact, fairness, ethics, and equity to ensure AI benefits all populations.	VA
24	Cobianchi L, Verde JM, Loftus TJ et al. Artificial intelligence and surgery: ethical dilemmas and open issues. J Am Coll Surg. 2022;235(2):268–275. doi: 10.1097/XCS.0000000000000242 [VA]	Consensus	12 experts	n/a	n/a	n/a	A multidisciplinary focus on implementation science and digital health education is needed to balance AI's opportunities with patient-centric ethics. Human skills like creativity remain essential in perioperative care and cannot be replicated by AI. Because model performance varies with target population and data, users must understand each tool's intended purpose, setting, and population. Ethical dilemmas should be addressed early in design and development, with performance monitoring continuing across the lifecycle.	IVB
25	van de Sande D, Van Genderen ME, Smit JM et al. Developing, implementing and governing artificial intelligence in medicine: a step-by-step approach to prevent an artificial intelligence winter. BMJ Health Care Inform. 2022;29(1):e100495. doi: 10.1136/bmjhci-2021-100495 [VA]	Literature Review	n/a	n/a	n/a	n/a	A framework for AI development and safe implementation was created by synthesizing current guidelines, regulations, good practices, and challenges in the AI literature. Following a structured implementation framework can improve adoption of AI-enabled technology in healthcare.	VA
26	Schwalbe N, Wahl B. Artificial intelligence and the future of global health. Lancet. 2020;395(10236):1579–1586. doi: 10.1016/S0140-6736(20)30226-9 [VA]	Literature Review	n/a	n/a	n/a	n/a	AI-driven health interventions could lead to improved health outcomes in LMICs. The global health community needs to work quickly to establish guidelines for development, testing, and use, and develop a user-driven research agenda to facilitate equitable and ethical use.	VA
27	Ethics and Governance of Artificial Intelligence for Health: WHO Guidance. World Health Organization (WHO); 2021. Accessed April 8, 2026. https://www.who.int/publications/i/item/9789240029200 [IVB]	Consensus	n/a	n/a	n/a	n/a	Six core principles for ethical health AI: (1) protect human autonomy; (2) promote well-being, safety, and the public interest; (3) ensure transparency, explainability, and intelligibility; (4) foster responsibility and accountability; (5) ensure inclusiveness and equity; and (6) promote responsive, sustainable AI.	IVB
28	Drabiak K, Kyzer S, Nemov V, El Naqa I. AI and machine learning ethics, law, diversity, and global impact. Br J Radiol. 2023;96(1150):20220934. doi: 10.1259/bjr.20220934 [VA]	Literature Review	n/a	n/a	n/a	n/a	The review describes emerging ethical challenges from AI/ML in clinical care and surveys regulatory and legal issues in Europe and the United States. It offers recommendations for trustworthy AI/ML that promote transparency, minimize bias and error, and protect patient well-being.	VA
29	Vollmer S, Mateen BA, Bohner G et al. Machine learning and artificial intelligence research for patient benefit: 20 critical questions on transparency, replicability, ethics, and effectiveness. BMJ. 2020;368:l6927. doi: 10.1136/bmj.l6927 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Proposes 20 questions to identify issues in AI/ML health applications, centered on transparency, reproducibility, ethics, and effectiveness (TREE). The checklist offers a framework for researchers, clinicians, patients, and others to critically evaluate AI/ML research.	VA
30	Crossnohere NL, Elsaid M, Paskett J, Bose-Brill S, Bridges JFP. Guidelines for artificial intelligence in medicine: literature review and content analysis of frameworks. J Med Internet Res. 2022;24(8):e36823. doi: 10.2196/36823 [VA]	Literature Review	n/a	n/a	n/a	n/a	Five oversight themes emerged for AI-enabled health technology: transparency, reproducibility, ethics, effectiveness, and engagement. Frameworks were less likely to address the surveillance phase of implementation and gave less attention to engaging clinical end users.	VA

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31	Omoumi P, Ducarouge A, Tournier A et al. To buy or not to buy—evaluating commercial AI solutions in radiology (the ECLAIR guidelines). Eur Radiol. 2021;31(6):3786–3796. doi: 10.1007/s00330-020-07684-x [VA]	Expert Opinion	n/a	n/a	n/a	n/a	A framework on questions and considerations for radiologists to evaluate the applicability and clinical utility of a commercially available AI-enabled technology before implementation	VA
32	Scott I, Carter S, Coiera E. Clinician checklist for assessing suitability of machine learning applications in healthcare. BMJ Health Care Inform. 2021;28(1):e100251. doi: 10.1136/bmjhci-2020-100251 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Clinicians should be able to critically evaluate AI-enabled technology before implementation. The authors developed 10 questions to help them assess the utility, feasibility, safety, and ethical use of an identified AI-enabled technology.	VA
33	Choudhury A. Toward an ecologically valid conceptual framework for the use of artificial intelligence in clinical settings: need for systems thinking, accountability, decision-making, trust, and patient safety considerations in safeguarding the technology and clinicians. JMIR Hum Factors. 2022;9(2):e35421. doi: 10.2196/35421 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Successful and safe adoption of AI in healthcare requires systems thinking, attention to clinician trust, cognitive workload, accountability, and patient safety. Without addressing these factors, AI tools risk being underutilized or misused, potentially compromising care quality.	VA
34	Generating Evidence for Artificial Intelligence Based Medical Devices: A Framework for Training Validation and Evaluation. World Health Organization; 2021. Accessed April 8, 2026. https://www.who.int/publications/i/item/9789240038462 [VA]	Consensus	n/a	n/a	n/a	n/a	The document guides development of safe, high-performing health AI, with ethical research and evidence generation at its core so all populations can benefit. Ethics, fairness, and data governance must be prioritized to prevent widening inequalities. User trust, user and patient experience, clinical-workflow integration, and patient-safety safeguards are crucial to adoption.	IVB
35	Regulatory Considerations on Artificial Intelligence for Health. World Health Organization; 2023. Accessed April 8, 2026. https://www.who.int/publications/i/item/9789240078871 [VA]	Consensus	n/a	n/a	n/a	n/a	WHO recognizes AI's potential to improve health outcomes by enhancing clinical trials, diagnosis, treatment, self-management, and person-centered care, and by building evidence and professional competence. With growing health-care data and rapid advances in analytics, AI could transform the health sector to meet diverse stakeholder needs across care and therapeutic development.	IVA
36	Hoelscher SH, Pugh A. N.U.R.S.E.S. embracing artificial intelligence: a guide to artificial intelligence literacy for the nursing profession. Nurs Outlook. 2025;73(4):102466. doi: 10.1016/j.outlook.2025.102466 [VA]	Literature Review	n/a	n/a	n/a	n/a	AI literacy is an essential competency for nurses. This skill will empower them to use emerging technology safely, ethically, and effectively in practice, education, and research. Authors developed a framework for nurses to lead responsible AI integration	VA
37	Badawy W, Zinhom H, Shaban M. Navigating ethical considerations in the use of artificial intelligence for patient care: a systematic review. Int Nurs Rev. 2025;72(3):e13059. doi: 10.1111/inr.13059 [IIIA]	Systematic Review	13 studies; 2020-2024	n/a	n/a	n/a	AI can benefit nursing practice but its integration potentially introduces ethical challenges (eg, privacy, accountability, transparency) that need to be addressed. Ethical governance frameworks are essential to ensure AI is adopted safely and responsibly.	IIIA
38	Warraich HJ, Tazbaz T, Califf RM. FDA perspective on the regulation of artificial intelligence in health care and biomedicine. JAMA[JAMA and JAMA Network Journals Full Text]. 2025;333(3):241–247. doi: 10.1001/jama.2024.21451 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	The FDA will continue to play a central role in ensuring safe, effective, and trustworthy AI tools to improve the lives of patients and clinicians alike. However, all involved entities will need to attend to AI with the rigor this transformative technology merits.	VA
39	Davis SE, Matheny ME, Balu S, Sendak MP. A framework for understanding label leakage in machine learning for health care. J Am Med Inform Assoc. 2023;31(1):274–280. doi: 10.1093/jamia/ocad178 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	The authors propose a framework to distinguish appropriate from inappropriate label leakage in ML development, helping ensure models are both statistically valid and clinically useful. Close collaboration among developers, evaluators, and clinician users is needed.	VA
40	Moons KGM, Damen JAA, Kaul T et al. PROBAST+AI: an updated quality, risk of bias, and applicability assessment tool for prediction models using regression or artificial intelligence methods. BMJ. 2025;388:e082505. doi: 10.1136/bmj-2024-082505 [VA]	Consensus	n/a	n/a	n/a	n/a	PROBAST+AI can be used by developers, researchers, editors, reviewers, clinicians, patients, ethics boards, guideline developers, and policy organizations to appraise the quality, risk of bias, and applicability of prediction models. It may reduce research waste while improving the accuracy, effectiveness, generalizability, use, and fairness of prediction models, including AI/ML.	IVA

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41	Kotp MH, Ismail HA, Basyouny HAA et al. Empowering nurse leaders: readiness for AI integration and the perceived benefits of predictive analytics. BMC Nurs. 2025;24(1):56. doi: 10.1186/s12912-024-02653-x [IIIA]	Qualitative	187 nurse leaders	n/a	n/a	readiness for AI integration and perceived benefits of AI-driven predictive analytics	Nursing leaders—especially those with advanced education and experience—are generally prepared to integrate AI, and their readiness positions them to improve outcomes and operational efficiency. However, further training and policy development are needed to fully realize AI's benefits in nursing practice.	IIIA
42	Alruwaili MM, Abuadas FH, Alsadi M et al. Exploring nurses' awareness and attitudes toward artificial intelligence: implications for nursing practice. Digit Health. 2024;10:20552076241271803. doi: 10.1177/20552076241271803 [IIIC]	Qualitative	220 registered nurses	n/a	n/a	awareness and attitude toward AI in healthcare	Healthcare and nursing administrators should raise nurses' awareness of AI applications and stress the value of integrating these technologies. Addressing nurses' concerns about AI control and discomfort is crucial, particularly given generational differences, as younger nurses often hold more positive attitudes. Change-management strategies may help overcome resistance.	IIIC
43	Chew HSJ, Achananuparp P. Perceptions and needs of artificial intelligence in health care to increase adoption: scoping review. J Med Internet Res. 2022;24(1):e32939. doi: 10.2196/32939 [VA]	Literature Review	n/a	n/a	n/a	n/a	The perceptions and needs of AI in its use in health care are crucial in improving its adoption by various stakeholders. Perceived utility and trustworthiness were associated with AI acceptability. Concerns for data security, privacy, and transparency should be considered to enhance adoption of AI	VA
44	Gombolay GY, Silva A, Schrum M et al. Effects of explainable artificial intelligence in neurology decision support. Ann Clin Transl Neurol. 2024;11(5):1224–1235. doi: 10.1002/acn3.52036 [IIB]	Quasi-experimental	365 participants (81 neurology, 284 general population)	explainable AI (xAI) decision support system	No explanation condition	Test performance, perceived explainability, trust, and social competence of the DSS, compliance, understandability, and agreement per question	More experienced neurologists performed worse when they perceived recommendations as more explainable, while the least experienced benefited in proportion to perceived explainability. Medical participants reported significantly lower trust in AI DSS and were less likely to accept advice they disagreed with.	IIB
45	Jungmann F, Jorg T, Hahn F et al. Attitudes toward artificial intelligence among radiologists, IT specialists, and industry. Acad Radiol. 2021;28(6):834–840. doi: 10.1016/j.acra.2020.04.011 [IIIB]	Qualitative	123 participants	n/a	n/a	Attitude toward the use of AI in clinical practice	Currently, a discrepancy exists between high expectations for the future role of AI and low confidence in the results. The demand for plausibility checks and the need to prove the usefulness in randomized controlled studies indicate what is needed in future research.	IIIB
46	Guideline for medical device and product evaluation. In: Guidelines for Perioperative Practice. AORN Inc; 2026:817–826. doi: 10.6015/c4y9j9 [IVA]	Guideline	n/a	n/a	n/a	n/a	Recommendations related to pre-purchase evaluations of medical devices and products.	IVA
47	Farah L, Borget I, Martelli N, Vallee A. Suitability of the current health technology assessment of innovative artificial intelligence–based medical devices: scoping literature review. J Med Internet Res. 2024;26:e51514. doi: 10.2196/51514 [VA]	Literature Review	n/a	n/a	n/a	n/a	A methodological HTA framework adapted for AI-based medical devices improves comparability of evaluations across jurisdictions and, by defining required expertise, supports a skilled workforce for robust HTAs. A comprehensive framework yields insights into efficacy, cost-effectiveness, and societal impact, guiding responsible implementation and maximizing patient and health-system benefit.	VA
48	Vasey B, Nagendran M, Campbell B et al. Reporting guideline for the early stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI. BMJ. 2022;377:e070904. doi: 10.1136/bmj-2022-070904 [IVA]	Consensus	n/a	n/a	n/a	n/a	The present statement provides a multi-stakeholder, consensus-based reporting guideline for the Developmental and Exploratory Clinical Investigations of DEcision support systems driven by Artificial Intelligence (DECIDE-AI).	IVA
49	Bektaş M, Chia CM, Burchell GL, Daams F, Bonjer HJ, van der Peet DL. Artificial intelligence–aided ultrasound imaging in hepatopancreatobiliary surgery: where are we now? Surg Endosc. 2024;38(9):4869–4879. doi: 10.1007/s00464-024-11130-0 [IIIA]	Systematic Review	11 nonexperimental studies; 2145 patients; 2001-2022	n/a	n/a	n/a	Ultrasound-based AI models show promising accuracy in predicting early tumoral recurrence and differentiating tissue types during and after hepatopancreatobiliary surgery. However, prospective studies are needed to confirm these results remain consistent and externally valid.	IIIA
50	Rony MKK, Parvin MR, Ferdousi S. Advancing nursing practice with artificial intelligence: enhancing preparedness for the future. Nurs Open. 2024;11(1). doi: 10.1002/nop2.2070 [VA]	Literature Review	n/a	n/a	n/a	n/a	Embracing AI can enhance nursing practice and improve patient outcomes. Successful implementation requires attention to technical integration and interoperability with existing systems and data formats, and nurses should be trained on the technology once it enters the workflow.	VA

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51	Canales C, Lee C, Cannesson M. Science without conscience is but the ruin of the soul: the ethics of big data and artificial intelligence in perioperative medicine. Anesth Analg. 2020;130(5):1234–1243. doi: 10.1213/ANE.0000000000004728 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Artificial intelligence promises improved safety and patient outcomes.We must evaluate the technical, ethical, and moral implications of artificial intelligence; bias, informed consent, data stewardship.	VA
52	Jain SS, Goto S, Hall JL et al. Pragmatic approaches to the evaluation and monitoring of artificial intelligence in health care: a science advisory from the American Heart Association. Circulation. 2025;152(23):e433–e442. doi: 10.1161/CIR.0000000000001400 [VA]	Consensus	n/a	n/a	n/a	n/a	Responsible use of AI involves evaluation and appropriate monitoring practices. A set of guiding questions was developed to frame the evaluation process in an actionable way for health systems to procure, deploy, and monitor the quality, value, and workforce impact of AI-enabled technology	IVB
53	Loftus TJ, Altieri MS, Balch JA et al. Artificial Intelligence-enabled decision support in surgery: state-of-the-art and future directions. Ann Surg. 2023;278(1):51–58. doi: 10.1097/SLA.0000000000005853 [IA]	Systematic Review	36 articles; sample size ranged from 163 - 2,882,526	n/a	n/a	n/a	AI-enabled decision support in surgery is limited by reliance on internal validation, small samples that risk overfitting and weaken predictive performance, and failure to report confidence intervals, precision, equity analyses, and clinical implementation. Researchers should improve scientific quality.	IA
54	Char DS, Burgart A. Machine-learning implementation in clinical anesthesia: opportunities and challenges. Anesth Analg. 2020;130(6):1709–1712. doi: 10.1213/ANE.0000000000004656 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Machine learning in clinical anesthesia could reduce clinician cognitive load, lower costs, and increase access to care. However, it poses challenges including skill atrophy, workflow disruption, clinician autonomy, and accountability for ML output. Successful integration requires careful consideration of these factors and thorough preparation.	VA
55	Wong A, Otles E, Donnelly JP et al. External validation of a widely implemented proprietary sepsis prediction model in hospitalized patients. JAMA Intern Med. 2021;181(8):1065–1070. doi: 10.1001/jamainternmed.2021.2626 [IIIA]	Nonexperimental	27697 hospitalized patients	sepsis prediction model	current clinical practice	Sepsis prediction score, time from prediction to antibiotic administration	External validation of a sepsis prediction model performed worse in the clinical setting with real-world patient data than reported by the developer. External validation of AI-enabled technology should be performed.	IIIA
56	Jones DT, Kerber KA. Artificial intelligence and the practice of neurology in 2035: The Neurology Future Forecasting Series. Neurology. 2022;98(6):238–245. doi: 10.1212/WNL.0000000000013200 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	AI could significantly transform neurology by 2035, but major challenges—including technical infrastructure readiness—must be addressed. Standards and system integration are essential, and outcomes will improve only with proper initial development and ongoing evaluation of AI interventions.	VA
57	Polce EM, Kunze KN, Dooley MS, Piuzzi NS, Boettner F, Sculco PK. Efficacy and applications of artificial intelligence and machine learning analyses in total joint arthroplasty: a call for improved reporting. J Bone Joint Surg Am. 2022;104(9):821–832. doi: 10.2106/JBJS.21.00717 [IIIA]	Systematic Review w/ Meta-Analysis	2014-2022; 55 studies	n/a	n/a	n/a	The performance of ML models was good to excellent when applied to a wide variety of clinically relevant outcomes in TJA. However, reporting of certain key methodological and model presentation criteria was inadequate.	IIIA
58	Software as a Medical Device: Possible Frameworks and Corresponding Considerations. International Medical Device Regulators Forum (IMDRF); 2014. Accessed April 8, 2026. https://www.imdrf.org/working-groups/software-medical-device-samd [IVB]	Guideline	n/a	n/a	n/a	n/a	Guidance for compliance with regulatory requirements for use of AI-enabled technology.	IVB
59	Gabriel RA, Harjai B, Simpson S, Goldhaber N, Curran BP, Waterman RS. Machine learning–based models predicting outpatient surgery end time and recovery room discharge at an ambulatory surgery center. Anesth Analg. 2022;135(1):159–169. doi: 10.1213/ANE.0000000000006015 [IIIA]	Nonexperimental	13,447 surgical procedures	ensemble learning predictive models	logistic regression model	Prediction of (1) surgery end time (2)PACU discharge time	Machine learning may be adapted by operating room management to allow for a better determination whether an add-on case at an outpatient surgery center could be adequately scheduled (ie, patient out of OR and discharged from PACU by end of day).	IIIA
60	Ranjbar A, Mork EW, Ravn J et al. Managing risk and quality of AI in healthcare: are hospitals ready for implementation? Risk Manag Healthc Policy. 2024;17:877–882. doi: 10.2147/RMHP.S452337 [VA]	Organizational Experience	Interviews with 15 experts	n/a	n/a	n/a	In less experienced endoscopists the use of CADe assistance increased adenoma detection and polyp parameters.	VA
61	Alsoof D, McDonald CL, Kuris EO, Daniels AH. Machine learning for the orthopaedic surgeon: uses and limitations. J Bone Joint Surg Am. 2022;104(17):1586–1594. doi: 10.2106/JBJS.21.01305 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Evaluating ML models is crucial before implementation—discrimination, calibration, fit to the use case, missing values, underrepresentation of patient groups, and whether results meaningfully change outcomes. ML has been used for preoperative outcome prediction.	VA

REFERENCE #	CITATION	EVIDENCE TYPE	SAMPLE SIZE/ POPULATION	INTERVENTION(S)	CONTROL/ COMPARISON	OUTCOME MEASURE(S)	CONCLUSION(S)	CONSENSUS
62	Kalpathy-Cramer J, Patel JB, Bridge C, Chang K. Basic artificial intelligence techniques: evaluation of artificial intelligence performance. Radiol Clin North Am. 2021;59(6):941–954. doi: 10.1016/j.rcl.2021.06.005 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Algorithm evaluation is critical to AI's clinical utility and robustness. Despite AI's promise across medical domains, careful evaluation is needed to produce high-performing, generalizable models, and external testing is a vital part of that evaluation.	VA
63	Andersen ES, Birk-Korch JB, Hansen RS et al. Monitoring performance of clinical artificial intelligence: a scoping review. JBI Evid Synth. 2024;22(12):2423–2446. doi: 10.11124/JBIES-24-00042 [VA]	Literature Review	n/a	n/a	n/a	n/a	Performance monitoring is crucial to ensure AI tools maintain discrimination, accuracy, calibration, and fairness; it can be done directly or by statistically detecting performance drift. Choosing a strategy requires balancing practical and ethical considerations. Guidance on which methods to use and how to weigh competing factors is lacking, so more research and testing is needed.	VA
64	Perkins ZB, Yet B, Sharrock A et al. Predicting the outcome of limb revascularization in patients with lower-extremity arterial trauma: development and external validation of a supervised machine-learning algorithm to support surgical decisions. Ann Surg. 2020;272(4):564–572. doi: 10.1097/SLA.0000000000004132 [IIIA]	Nonexperimental	Observed 508 limbs from US joint trauma system and 51 limbs from UK Joint Theatre Trauma Registry	Prompt revascularization of ischemic tissues	n/a	Predicting failed revascularization and subsequent limb viability	The Bayesian network (BN) can accurately predict the outcome of limb revascularization at the time of initial wound evaluation, supporting rational treatment decisions and establishing sensible treatment expectations.	IIIA
65	van de Sande D, van Genderen ME, Verhoef C et al. Optimizing discharge after major surgery using an artificial intelligence–based decision support tool (DESIRE): an external validation study. Surgery. 2022;172(2):663–669. doi: 10.1016/j.surg.2022.03.031 [IIIA]	Nonexperimental	Adult gastro and oncology surgery patients admitted to 3 hospitals more than 2 days after initial surgery.	n/a	n/a	AUROC, sensitivity, specificity, PPV, NPV	A machine-learning model trained on local patient data predicted safe discharge across surgical populations and settings. Given its high accuracy, workflow integration could expedite discharge and ease hospital capacity by reducing avoidable bed-days.	IIIA
66	Bektas M, Reiber BMM, Pereira JC, Burchell GL, van der Peet DL. Artificial intelligence in bariatric surgery: current status and future perspectives. Obes Surg. 2022;32(8):2772–2783. doi: 10.1007/s11695-022-06146-1 [IIIA]	Systematic Review	10 restrospective, 1 cohort study; 1821 patients; 2007-2021	n/a	n/a	n/a	Machine-learning algorithms show promise for predicting outcomes after bariatric surgery, but clinical use depends on external validation. Predictions may help inform decisions about the type and timing of surgery and postoperative complications.	IIIA
67	Graafsma J, Murphy RM, van de Garde EMW et al. The use of artificial intelligence to optimize medication alerts generated by clinical decision support systems: a scoping review. J Am Med Inform Assoc. 2024;31(6):1411–1422. doi: 10.1093/jamia/ocae076 [VA]	Literature Review	n/a	n/a	n/a	n/a	AI-based methods can be used to optimize medication alerts in a hospital setting. However, reporting on models' development and validation should be improved, and external validation and implementation in hospital practice should be encouraged.	VA
68	Gurung B, Liu P, Harris PDR et al. Artificial intelligence for image analysis in total hip and total knee arthroplasty a scoping review. Bone Joint J. 2022;104-B(8):929–937. doi: 10.1302/0301-620X.104B8.BJJ-2022-0120.R2 [VB]	Literature Review	n/a	n/a	n/a	n/a	AI shows promise in image analysis of hip and knee implants to measure malposition and features of loosening hip imlants, but requires further research for real-world application including external validation	VB
69	van der Stigchel B, van den Bosch K, van Diggelen J, Haselager P. Intelligent decision support in medical triage: are people robust to biased advice? J Public Health (Oxf). 2023;45(3):689–696. doi: 10.1093/pubmed/fdad005 [IIB]	Quasi-experimental	34 participants	Agent providing biased advice	Non-biased agent	Participants' ability to detect and neutralize bias from the agent	Insufficient human control can result in inability to detect and prevent machine biases	IIB
70	Ball Dunlap PA, Nahm ES, Umberfield EE. Data-centric machine learning in nursing: a concept clarification. Comput Inform Nurs. 2024;42(5):325–333. doi: 10.1097/CIN.0000000000001102 [VA]	Literature Review	n/a	n/a	n/a	n/a	A data-centric machine-learning approach emphasizes data quality and iterative improvement during development to achieve high-performing models that benefit clinical care processes and workflows. This requires a well-defined problem, a high-quality dataset, and data governance and compliance.	VA
71	Alenezi A, Alshammari MH, Ibrahim IA. Optimizing nursing productivity: exploring the role of artificial intelligence, technology integration, competencies, and leadership. J Nurs Manag. 2024;2024:8371068. doi: 10.1155/2024/8371068 [IIIA]	Nonexperimental	329 nurses	n/a	n/a	productivity, technology integration, workforce competency	Effective technology integration can boost productivity, though AI may reduce it initially. Developing nursing competence can mediate this and maximize AI's positive impact; integration requires training to equip nurses with skills to use AI-enabled technology effectively.	IIIA
72	Abraham J, Bartek B, Meng A et al. Integrating machine learning predictions for perioperative risk management: towards an empirical design of a flexible-standardized risk assessment tool. J Biomed Inform. 2023;137:104270. doi: 10.1016/j.jbi.2022.104270 [IIIA]	Qualitative	17 clinicians	n/a	n/a	Risk ranking comparisons (ML to clinician), preferences for tool display and content, potential impact of ML tool on clinical workflow	Clinician feedback on design requirements and preferences for an AI-enabled technology can enhance usability and user acceptance. With this model, user refinements can enhance understanding of a patient's postoperative risks, improve risk detection, and encourage preemptive management.	IIIA

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73	King CR, Shambe A, Abraham J. Potential uses of AI for perioperative nursing handoffs: a qualitative study. JAMIA Open. 2023;6(1):ooad015. doi: 10.1093/jamiaopen/ooad015 [IIIB]	Qualitative	11 nurses participated in semistructured interviews	n/a	n/a	usefulness and applicability of AI integration into nursing workflows	Well-designed AI tools could aid postoperative nursing handoffs by flagging a patient's specific elevated risks and prompting discussion. Successful integration requires understanding user experience and workflows, and personalization may be beneficial.	IIIB
74	von Gerich H, Moen H, Block LJ et al. Artificial intelligence–based technologies in nursing: a scoping literature review of the evidence. Int J Nurs Stud. 2022;127:104153. doi: 10.1016/j.ijnurstu.2021.104153 [VA]	Literature Review	n/a	n/a	n/a	n/a	Nurses are not being included early or often enough in the development phase of AI-enabled technology. AI research also lacks comprehensive evaluation of outcomes. Evaluation of implementation measures and clinical outcomes should be a focus for future AI research	VA
75	Guideline for team communication. In: Guidelines for Perioperative Practice. AORN Inc; 2026:1163–1198. doi: 10.6015/q5c8q6 [IVA]	Guideline	n/a	n/a	n/a	n/a	Guidance for culture of safety and team communication	IVA
76	Barua I, Vinsard DG, Jodal HC et al. artificial intelligence for polyp detection during colonoscopy: a systematic review and meta-analysis. Endoscopy. 2021;53(3):277–284. doi: 10.1055/a-1201-7165 [IA]	Systematic Review w/ Meta-Analysis	5 RCTs; 2019-2020; 4311 patients	n/a	n/a	n/a	AI-based polyp detection systems during colonoscopy increase detection of small nonadvanced adenomas and polyps, but not of advanced adenomas. Further research and development is needed to increase detection of advanced adenomas. Withdrawal time was increased with AI use.	IA
77	Aziz M, Haghbin H, Sayeh W et al. Comparison of artificial intelligence with other interventions to improve adenoma detection rate for colonoscopy: a network meta-analysis. J Clin Gastroenterol. 2024;58(2):143–155. doi: 10.1097/MCG.0000000000001813 [IA]	Systematic Review w/ Meta-Analysis	94 RCTs, 61,172 pts; 2007-2022	n/a	n/a	n/a	Compared to HD colonoscopy, distal attachments, balloon/retrograde endoscopes, other imaging techniques AI improved ADR when compared with most endoscopic interventions. Future RCTs directly assessing these associations are encouraged.	IA
78	Bellini V, Russo M, Domenichetti T, Panizzi M, Allai S, Bignami EG. Artificial intelligence in operating room management. J Med Syst. 2024;48(1):19. doi: 10.1007/s10916-024-02038-2 [IIIC]	Systematic Review	1 RCT, 21 nonexperimental studies; 2019-2023	n/a	n/a	n/a	The integration of artificial intelligence in operating room management promises to enhance healthcare efficiency by predicting surgical case duration, PACU length of stay, and surgical case cancellation. Challenges such as data access and privacy concerns need to be addressed.	IIIC
79	Susam F. Artificial intelligence–driven innovation in cancer surgery: a systematic review of Horizon Europe–funded projects. Forbes J Med. 2024;5(1):9–19. doi: 10.4274/forbes.galenos.2023.38278 [IIIA]	Systematic Review	n/a	n/a	n/a	n/a	The analyzed projects could significantly advance cancer surgery by improving precision, personalizing treatment, and automating procedures. Continued research and development are needed to address data integration, algorithmic transparency, and clinical implementation.	IIIA
80	Altaf A, Endo Y, Guglielmi A et al. Upfront surgery for intrahepatic cholangiocarcinoma: prediction of futility using artificial intelligence. Surgery. 2025;179:108809. doi: 10.1016/j.surg.2024.06.059 [IIIA]	Nonexperimental	827 patients	ensemble AI model	three ML algorithms, 1 Deep learning (DL) model	Futility (mortality or recurrence within 12 months of surgery)	An ensemble model accurately identified patients at high risk of futile surgery for intrahepatic cholangiocarcinoma preoperatively. Such AI prediction models can give clinicians reliable preoperative guidance and help avoid surgeries unlikely to provide long-term benefit.	IIIA
81	Bellini V, Valente M, Turetti M et al. Current applications of artificial intelligence in bariatric surgery. Obes Surg. 2022;32(8):2717–2733. doi: 10.1007/s11695-022-06100-1 [VB]	Literature Review	n/a	n/a	n/a	n/a	Artificial intelligence algorithms have been used in each step of the perioperative path of the patient candidates for bariatric surgery, from the presurgical evaluation and risk-assessment to postoperative complications and outcomes prediction.	VB
82	Dhingra LS, Sangha V, Aminorroaya A et al. A multicenter evaluation of the impact of therapies on deep learning–based electrocardiographic hypertrophic cardiomyopathy markers. Am J Cardiol. 2025;237:35–40. doi: 10.1016/j.amjcard.2024.11.028 [IIIB]	Nonexperimental	351 patients	Surgical or percutaneous reduction of the interventricular septum (SRT) and mavacamten	Patients receiving therapy with mavacamten	AI-ECG HCM score before and after SRT and mavacamten therapy	AI-ECG evaluation of ECG images can effectively monitor treatment response in HCM patients, particularly with mavacamten showing significant improvement compared to surgical SRT.	IIIB
83	Kooi K, Talavera E, Freundt L et al. From data to decisions: how artificial intelligence is revolutionizing clinical prediction models in plastic surgery. Plast Reconstr Surg. 2024;154(6):1341–1352. doi: 10.1097/PRS.0000000000011266 [VB]	Literature Review	n/a	n/a	n/a	n/a	The authors summarize adopting a systematic approach to developing and validating AI in clinical use. The TRIPOD-AI and PROBAST tools can enhance transparency, accuracy, and reliability of AI-based model in plastic surgery.	VB
84	Mendo IR, Marques G, de la Torre Díez I, López-Coronado M, Martín-Rodríguez F. Machine learning in medical emergencies: a systematic review and analysis. J Med Syst. 2021;45(10):88. doi: 10.1007/s10916-021-01762-3 [IIIA]	Systematic Review w/ Meta-Analysis	2017-2021; 20 studies, 12 mobile apps	n/a	n/a	n/a	Machine learning is increasingly applicable to healthcare, offering ways to improve efficiency and quality. With mobile health devices and apps that use data to assess real-time health, ML is a growing trend in the industry.	IIIA

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85	Nemani S, Goyal S, Sharma A, Kothari N. Artificial intelligence in pediatric airway – a scoping review. Saudi J Anaesth. 2024;18(3):410–416. doi: 10.4103/sja.sja_110_24 [VA]	Literature Review	n/a	n/a	n/a	n/a	AI can support decision-making, but predictions must be corroborated by anesthesiologists' clinical judgment. In pediatric airway management, AI enhances preoperative assessment, intraoperative decisions, and complication prediction via machine learning and predictive algorithms. Realizing its potential to improve outcomes requires aligning AI with clinical expertise and ongoing collaboration.	VA
86	Senda A, Endo A, Kinoshita T, Otomo Y. Development of practical triage methods for critical trauma patients: machine-learning algorithm for evaluating hybrid operation theatre entry of trauma patients (THETA). Eur J Trauma Emerg Surg. 2022;48(6):4755–4760. doi: 10.1007/s00068-022-02002-0 [IIIA]	Nonexperimental	117,771 trauma patients with an abbreviated injury scale (AIS) > 3.	A machine-learning-based triage algorithm	The performance of the proposed model was compared against those of other statistical models [logistic regression and classification and regression tree (CART) models] while considering the status quo entry condition (systolic blood pressure < 90 mmHg).	Trauma patient triage entry to hybrid OR	A machine-learning-based algorithm was developed to triage patient entry into hybrid operating rooms. Although the validation in a prospective multicentre arrangement is warranted, the proposed algorithm could be a potentially useful tool in clinical practice.	IIIA
87	Seong H, Lee KS, Choi Y et al. Explainable artificial intelligence for predicting red blood cell transfusion in geriatric patients undergoing hip arthroplasty: machine learning analysis using national health insurance data. Medicine (Baltimore). 2024;103(8):e36909. doi: 10.1097/MD.0000000000036909 [IIIA]	Nonexperimental	19,110 patients aged 65 years or more with hip arthroplasty in 2019	Machine learning analysis	n/a	Top predictors of risk	Machine learning is an effective prediction model for blood transfusion among patients with hip arthroplasty. The high-risk group with anemia, age and comorbid conditions need to be treated with tranexamic acid, iron and/or other appropriate interventions.	IIIA
88	Thurston MDV, Kim DH, Wit HK. Neural network detection of pacemakers for MRI safety. J Digit Imaging. 2022;35(6):1673–1680. doi: 10.1007/s10278-022-00663-2 [IIIA]	Nonexperimental	3996 with pacemakers visible and 3977 without	Retrained a pre-trained image classification neural network	Manual review by two board certified radiologists	Accuracy of neural network model in classifying presence of pacemakers	Neural network image classification can effectively screen for the presence of cardiac devices to improve MRI safety	IIIA
89	Wirries A, Geiger F, Hammad A, Oberkircher L, Blümcke I, Jabari S. Artificial intelligence facilitates decision-making in the treatment of lumbar disc herniations. Eur Spine J. 2021;30(8):2176–2184. doi: 10.1007/s00586-020-06613-2 [IIIB]	Nonexperimental	60 patients	33 patients surgically treated	27 patients conservatively treated	Oswestry Disability Index after 6 months	Supervised deep learning models can identify patients at an early stage who would benefit from conservative therapy, and on the contrary avoid painful and unnecessary delays for patients who would profit from surgical therapy.	IIIB
90	Hashimoto DA, Witkowski E, Gao L, Meireles O, Rosman G. Artificial intelligence in anesthesiology: current techniques, clinical applications, and limitations. Anesthesiology. 2020;132(2):379–394. doi: 10.1097/ALN.0000000000002960 [VB]	Literature Review	n/a	n/a	n/a	n/a	AI has the potential to affect anesthesia practice across depth-of-anesthesia monitoring, anesthesia control, event and risk prediction, ultrasound guidance, pain management, and OR logistics. The current focus is not on replacing clinician judgment or skills but on augmenting them, with interdisciplinary collaboration guiding the strategy for optimal use.	VB
91	Estrada Alamo CE, Diatta F, Monsell SE, Lane-Fall MB. Artificial intelligence in anesthetic care: a survey of physician anesthesiologists. Anesth Analg. 2024;138(5):938–950. doi: 10.1213/ANE.0000000000006752 [IIIB]	Qualitative	1086 anesthesiologists	n/a	n/a	Attitude toward the use of AI in clinical practice	Understanding anesthesiologists' perspectives on AI is essential for the effective integration of AI into anesthesiology, as AI has the potential to revolutionize the field. Health care organizations need to develop policies related to AI to address potential barriers to using AI.	IIIB
92	Chen D, Wu L, Li Y et al. Comparing blind spots of unsedated ultrafine, sedated, and unsedated conventional gastroscopy with and without artificial intelligence: a prospective, single-blind, 3-parallel-group, randomized, single-center trial. Gastrointest Endosc. 2020;91(2):332–339. doi: 10.1016/j.gie.2019.09.016 [IC]	RCT	437 patients	EGD with AI assistance (3 subgroups)	conventional EGD (C-EGD) without AI assistance (3 subgroups)	Difference in blind spot rate between subgroups (AI vs non-AI) and across subgroups	Sedated C-EGD had the lowest blind-spot rate of the three EGD types, and adding AI maximally reduced blind spots on sedated C-EGD. AI use mitigates skill variation among endoscopists and can serve as training to improve endoscopy quality.	IC

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93	Ruskin KJ, Corvin C, Rice SC, Winter SR. Autopilots in the operating room: safe use of automated medical technology. Anesthesiology. 2020;133(3):653–665. doi: 10.1097/ALN.0000000000003385 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Clinicians should receive training in human-system interaction, including vigilance, management of system failures, and maintaining manual skills. Medical device manufacturers should be encouraged to develop comprehensive training materials that describe possible system failures.	VA
94	Wild C, Lang F, Gerhäuser AS et al. Telestration with augmented reality for visual presentation of intraoperative target structures in minimally invasive surgery: a randomized controlled study. Surg Endosc. 2022;36(10):7453–7461. doi: 10.1007/s00464-022-09158-1 [IB]	RCT	60 laparoscopic novices	Group 2 trained with additional telestration with AR on the operative screen first and then only with verbal guidance in the second round	Group 1 trained only with verbal guidance first and then with additional telestration with AR on the operative screen in the second round	Time needed for training, performance with GOALS and OSATS score for LC, complications, and subjective workload (NASA-TLX questionnaire)	The iSurgeon system was developed to provide visual guidance in the operating room by telestration with augmented reality (AR).Telestration with AR improves training success and safety in MIS.	IB
95	Wijnberge M, Geerts BF, Hol L et al. Effect of a machine learning–derived early warning system for intraoperative hypotension vs standard care on depth and duration of intraoperative hypotension during elective noncardiac surgery: The HYPE randomized clinical trial. JAMA[JAMA and JAMA Network Journals Full Text]. 2020;323(11):1052–1060. doi: 10.1001/jama.2020.0592 [IA]	RCT	60 patients	Early warning system	Standard care	Depth and duration of intraoperative hypotension; treatment behavior;	A machine-learning-derived early warning system reduced intraoperative hypotension compared with standard care. Larger studies in diverse settings are needed to understand effects on additional outcomes and to fully assess safety and generalizability.	IA
96	Wangpitipanit S, Lininger J, Anderson N. Exploring the deep learning of artificial intelligence in nursing: a concept analysis with Walker and Avant's approach. BMC Nurs. 2024;23(1):529. doi: 10.1186/s12912-024-02170-x [VA]	Literature Review	n/a	n/a	n/a	n/a	A summary of deep learning in nursing and its practice implications. Future research should examine its impact on healthcare operations through quantitative and qualitative study, and a framework is recommended to guide integration into nursing practice.	VA
97	Mello MM, Guha N. Understanding liability risk from using health care artificial intelligence tools. N Engl J Med. 2024;390(3):271–278. doi: 10.1056/NEJMhle2308901 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Decisions to adopt and lifecycle monitoring of AI should reflect the potential risk of each AI tool individually. It is prudent to inform patients when AI models are used in diagnostic or treatment decisions.	VA
98	Loftus TJ, Tighe PJ, Filiberto AC et al. Artificial intelligence and surgical decision-making. JAMA Surg. 2020;155(2):148–158. doi: 10.1001/jamasurg.2019.4917 [VA]	Literature Review	n/a	n/a	n/a	n/a	Integrating AI into surgical decision-making could transform care by augmenting the decision to operate, informed consent, identification and mitigation of modifiable risk factors, postoperative management decisions, and shared decisions about resource use.	VA
99	Allen B, Dreyer K, Stibolt R Jr et al. Evaluation and real-world performance monitoring of artificial intelligence models in clinical practice: try it, buy it, check it. J Am Coll Radiol. 2021;18(11):1489–1496. doi: 10.1016/j.jacr.2021.08.022 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Regulatory clearance alone may not be sufficient to guarantee the safety and efficacy of AI algorithms in all radiological practices. It is important to evaluate and monitor AI models to ensure they maintain performance and patient safety.	VA
100	Meier LJ, Hein A, Diepold K, Buyx A. Algorithms for ethical decision-making in the clinic: a proof of concept. Am J Bioeth. 2022;22(7):4–20. doi: 10.1080/15265161.2022.2040647 [IIB]	Quasi-experimental	69 cases	Algorithm based on Beauchamp and Childress' prima-facie principles	n/a	Recommendations for ethical decision-making	The algorithm can generate reasonable recommendations based on learned examples, but it requires further refinement and expansion of the dataset.	IIB
101	Naor GM, Tocut M, Moalem M et al. Screening for medication errors and adverse events using outlier detection screening algorithms in an inpatient setting. J Med Syst. 2022;46(12):88. doi: 10.1007/s10916-022-01864-6 [IIIB]	Nonexperimental	Retrospective phase: 226,804 medical orders, Prospective phase: 25,625 medical orders	Outlier detection screening algorithms using MedAware software system	n/a	Clinical relevance of alerts and change in prescriber behavior	The system generated accurate and clinically valid alerts with low alert burden, enabling physicians to improve daily medical practice.	IIIB
102	Podrat JL, Ramirez Del Val F, Pei KY. Evolution of risk calculators and the dawn of artificial intelligence in predicting patient complications. Surg Clin North Am. 2021;101(1):97–107. doi: 10.1016/j.suc.2020.08.012 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	The incorporation of artificial intelligence into risk calculators can improve the accuracy and usability of these tools in predicting patient complications and mortality, but further study is needed.	VA
103	Rellum SR, Schuurmans J, van der Ven WH et al. Machine learning methods for perioperative anesthetic management in cardiac surgery patients: a scoping review. J Thorac Dis. 2021;13(12):6976–6993. doi: 10.21037/jtd-21-765 [VA]	Literature Review	n/a	n/a	n/a	n/a	ML models in perioperative anesthetic management of cardiac surgery patients show promising results, especially when integrating dynamic parameters. The impact on clinical outcomes of ML integration have yet to be determined.	VA

REFERENCE #	CITATION	EVIDENCE TYPE	SAMPLE SIZE/ POPULATION	INTERVENTION(S)	CONTROL/ COMPARISON	OUTCOME MEASURE(S)	CONCLUSION(S)	CONSENSUS
104	Ahmad A, Wilson A, Haycock A et al. Evaluation of a real-time computer-aided polyp detection system during screening colonoscopy: AI-DETECT study. Endoscopy. 2023;55(4):313–319. doi: 10.1055/a-1966-0661 [IB]	RCT	614 patients	Computer-aided detection (CADe) system	Standard colonoscopy	Polyp detection rate (PDR) and adenoma detection rate (ADR), procedure time, SP6 score (# of adenomas and SSLs per 6-minute withdrawal time)	CADe improved PDR (85.7% vs 79.7%, P=0.05) but not ADR (71.4% vs 65.0%, P=0.09) among experienced colonoscopists, with no difference in procedure time or SP6. Benefit may be greatest for low detectors and trainees; algorithm choice may contribute to variation between studies.	IB
105	Adeoye J, Su YX. Leveraging artificial intelligence for perioperative cancer risk assessment of oral potentially malignant disorders. Int J Surg. 2024;110(3):1677–1686. doi: 10.1097/JS9.0000000000000979 [VA]	Literature Review	n/a	n/a	n/a	n/a	AI may offer better surgical risk stratification for oral potentially malignant disorders (OPMDs) than current dysplasia assessment and grading. However, AI models developed for this purpose are not yet streamlined enough for current clinical surgical application.	VA
106	Gray M, Samala R, Liu Q et al. Measurement and mitigation of bias in artificial intelligence: a narrative literature review for regulatory science. Clin Pharmacol Ther. 2023;115(4):687–697. doi: 10.1002/cpt.3117 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	The authors stress understanding, detecting, and mitigating AI bias—especially in healthcare—to avoid serious harm. Mitigation should begin at solution initiation, engage end users through development and implementation, and continue with post-deployment monitoring.	VA
107	Gichoya JW, Thomas K, Celi LA et al. AI pitfalls and what not to do: mitigating bias in AI. Br J Radiol. 2023;96(1150):20230023. doi: 10.1259/bjr.20230023 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Bias arises across the AI lifecycle and must be addressed at each step, from problem definition through post-deployment monitoring. This requires diverse, representative datasets, rigorous testing and validation, and ongoing monitoring and evaluation of health AI performance.	VA
108	Sendak M, Balu S, Hernandez AF. Proactive algorithm monitoring to ensure health equity. JAMA Netw Open. 2023;6(12):e2345022. doi: 10.1001/jamanetworkopen.2023.45022 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Health care organizations and the health care industry must be held accountable for harm and discrimination caused by biased AI and algorithms.	VA
109	Coyner AS, Singh P, Brown JM et al. Association of biomarker-based artificial intelligence with risk of racial bias in retinal images. JAMA Ophthalmol. 2023;141(6):543–552. doi: 10.1001/jamaophthalmol.2023.1310 [IIIB]	Nonexperimental	4095 retinal fundus images collected from 245 neonates	Retinal vessel maps (RVMs)	Color fundus photographs	Area under the precision-recall curve (AUC-PR) and area under the receiver operating characteristic curve (AUROC) for classification of self-reported race (SRR)	Removing information relevant to self-reported race from fundus photographs can be very challenging, and preprocessing steps may fail to remove race-associated features. Potential bias should be evaluated during training as much as preprocessing, and model performance should be assessed across all subpopulations for whom the model will be implemented.	IIIB
110	Zaribafzadeh H, Webster WL, Vail CJ et al. Development, deployment, and implementation of a machine learning surgical case length prediction model and prospective evaluation. Ann Surg. 2023;278(6):890–895. doi: 10.1097/SLA.0000000000005936 [IIIB]	Nonexperimental	107,898 procedures	Gradient-boosted decision tree model to predict surgical procedure length	Schedulers predicted procedure length	Prediction accuracy of surgical procedure length, over and under-prediction errors	The model outperformed schedulers, predicting more procedures within 20% of the actual procedure length and reducing underprediction errors.	IIIB
111	Feng J, Phillips RV, Malenica I et al. Clinical artificial intelligence quality improvement: towards continual monitoring and updating of AI algorithms in healthcare. NPJ Digit Med. 2022;5(1):66. doi: 10.1038/s41746-022-00611-y [VA]	Expert Opinion	n/a	n/a	n/a	n/a	The authors advocate hospital AI quality-improvement (AI-QI) units for algorithm quality assurance, propose statistical frameworks for monitoring AI performance, and outline considerations for model-updating procedures. They note a lack of available software for monitoring and maintaining AI algorithms.	VA
112	Global Strategy on Digital Health 2020-2025. World Health Organization; 2021. Accessed April 8, 2026. https://www.who.int/publications/i/item/9789240020924 [IVB]	Consensus	n/a	n/a	n/a	n/a	Recommendations made for monitoring practices for digital health technologies, and preparation of health workers for deploying and using digital health technologies	IVB
113	Rivera SC, Liu X, Chan AW, Denniston AK, Calvert MJ; SPIRIT-AI and CONSORT-AI Working Group. Guidelines for clinical trial protocols for interventions involving artificial intelligence: the SPIRIT-AI Extension. BMJ. 2020;370:m3210. doi: 10.1136/bmj.m3210 [IIIA]	Nonexperimental	103 stakeholders in Delphi survey, 31 stakeholders in consensus meeting, 34 participants in checklist pilot	n/a	n/a	n/a	The SPIRIT-AI extension provides international consensus guidance on AI-specific information to report in clinical trial protocols, alongside SPIRIT 2013. It comprises 15 items—3 elaborations of existing SPIRIT 2013 guidance for AI trials and 12 new extensions—aimed at promoting transparency in trial design and methods to aid understanding, interpretation, and peer review.	IIIA

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114	Larson DB, Magnus DC, Lungren MP, Shah NH, Langlotz CP. Ethics of using and sharing clinical imaging data for artificial intelligence: a proposed framework. Radiology. 2020;295(3):675–682. doi: 10.1148/radiol.2020192536 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	The authors argue clinical data should be treated as a public good for the benefit of future patients, and that all individuals and entities with data access should act as data stewards with fiduciary duties to safeguard privacy and ensure data availability for knowledge development.	VA
115	Liebrenz M, Bhugra D, Alibudbud R, Ventriglio A, Smith A. AI in health care and the fragile pursuit of equity and social justice. Lancet. 2024;404(10455):843. doi: 10.1016/S0140-6736(24)01604-0 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Medical AI should serve public health and be piloted and validated across diverse socioeconomic and cultural settings to promote equity and inclusivity. Mandatory algorithmic transparency and fair-use provisions would enable local refinement and accountability, potentially mitigating cost barriers in low-income regions.	VA
116	Rogers WA, Draper H, Carter SM. Evaluation of artificial intelligence clinical applications: detailed case analyses show value of healthcare ethics approach in identifying patient care issues. Bioethics. 2021;35(7):623–633. doi: 10.1111/bioe.12885 [VA]	Case Report	n/a	n/a	n/a	n/a	Describes an ethical evaluation for two AI based systems for clinical decision support.	VA
117	Chen Z, Chen C, Yang G et al. Research integrity in the era of artificial intelligence: challenges and responses. Medicine (Baltimore). 2024;103(27):e38811. doi: 10.1097/MD.0000000000038811 [VB]	Literature Review	n/a	n/a	n/a	n/a	The review concludes that the rapid advancement of AI technology necessitates the development and enforcement of comprehensive guidelines and training to maintain research integrity and public trust in science. International collaboration is essential for developing unified ethical standards.	VB
118	Mittelstadt BD, Allo P, Taddeo M, Wachter S, Floridi L. The ethics of algorithms: mapping the debate. Big Data & Society. 2016;3(2). doi: 10.1177/2053951716679679 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Algorithms increasingly mediate decisions in digital life, raising ethical concerns. The authors propose a conceptual map organizing these into epistemic, normative, and traceability issues, which should be addressed in an interdisciplinary, multidimensional way for ethical design, deployment, and governance.	VA
119	Rochon M, Jurkiewicz J, Morais C, Gondo T. Using artificial intelligence to improve wound image quality: a feasibility study. Wounds UK. 2020;16(4):54–59. [IIIA]	Nonexperimental	266 wound images	Artificial intelligence model for detecting image blur	n/a	Percentage of false positive and false negative blur detections	Using AI to detect image blur can improve the quality of wound images, which is critical for clinical decision-making and patient confidence.	IIIA
120	Resnik DB, Hosseini M. The ethics of using artificial intelligence in scientific research: new guidance needed for a new tool. AI Ethics. 2025;5(2):1499–1521. doi: 10.1007/s43681-024-00493-8 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Explores the ethical implications of using AI in scientific research. It provides a comprehensive analysis of the benefits, challenges, and ethical considerations, and concludes with a set of recommendations for responsible AI use in science.	VA
121	Nikolic B. Racial bias exacerbated through AI: An example using chest radiograph models. Radiology. 2023;309(2):e232666. doi: 10.1148/radiol.232666 [VB]	Expert Opinion	n/a	n/a	n/a	n/a	Highlights racial bias in AI models for chest radiograph diagnosis, with higher underdiagnosis rates for Black, Hispanic/Latino, and Asian patients than White patients. Findings stress the need for more granular, accurate racial and ethnic categorization to avoid misdiagnosis and ensure equity.	VB
122	O'Connor S, Booth RG. Algorithmic bias in health care: opportunities for nurses to improve equality in the age of artificial intelligence. Nurs Outlook. 2022;70(6):780–782. doi: 10.1016/j.outlook.2022.09.003 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	The authors concluded that algorithmic bias in AI can exacerbate existing inequalities in health care and emphasized the need for nurses to be educated about AI and its ethical implications to improve patient care and service delivery.	VA
123	Uche-Anya E, Anyane-Yeboa A, Berzin TM, Ghassemi M, May FP. Artificial intelligence in gastroenterology and hepatology: how to advance clinical practice while ensuring health equity. Gut. 2022;71(9):1909–1915. doi: 10.1136/gutjnl-2021-326271 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Addressing biases in AI development is critical for ensuring health equity.	VA
124	Tejani AS, Retson TA, Moy L, Cook TS. Detecting common sources of AI bias: questions to ask when procuring an AI solution. Radiology. 2023;307(3):e230580. doi: 10.1148/radiol.230580 [VB]	Expert Opinion	n/a	n/a	n/a	n/a	Authors discuss the importance of understanding sources of bias in AI model development and emphasize the need for diverse training data sets to mitigate AI bias. Critical evaluation and monitoring of AI performance after deployment are necessary to identify additional sources of bias.	VB
125	Morris MX, Song EY, Rajesh A, Asaad M, Phillips BT. Ethical, legal, and financial considerations of artificial intelligence in surgery. Am Surg. 2023;89(1):55–60. doi: 10.1177/00031348221117042 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Need to acknowledge and address the ethical, financial, and legal implications of using artificial intelligence for patient care to uphold the standard of care and patient-provider trust. Thoughtful and balanced use of AI can potentially address or mitigate clinician bias as well.	VA

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126	Chen C, Chen Z, Luo W et al. Ethical perspective on AI hazards to humans: a review. Medicine (Baltimore). 2023;102(48):e36163. doi: 10.1097/MD.0000000000036163 [VC]	Literature Review	n/a	n/a	n/a	n/a	While AI holds tremendous potential across fields, it also brings dangers and challenges. Extensive research and analysis—plus corresponding regulatory and normative measures—are needed to ensure safety and reliability while safeguarding public rights and interests.	VC
127	Urbina JT, Vu PD, Nguyen MV. Disability ethics and education in the age of artificial intelligence: identifying ability bias in ChatGPT and Gemini. Arch Phys Med Rehabil. 2025;106(1):14–19. doi: 10.1016/j.apmr.2024.08.014 [IIIB]	Nonexperimental	300 generated descriptions from chatbots	Descriptions of people, patients, and athletes with a disability	Descriptions of people without a disability	Linguistic analysis of favorable and limiting words	Generative AI chatbots demonstrate quantifiable ability bias and often exclude people with disabilities in responses.	IIIB
128	Duffourc MN, Gerke S. Health care AI and patient privacy – Dinerstein v Google. JAMA[JAMA and JAMA Network Journals Full Text]. 2024;331(11):909–910. doi: 10.1001/jama.2024.1110 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Disclosure and privacy practices should accurately reflect data-sharing activities that use patient's EHR data. EHR data should be sufficiently de-identified before sharing. Obtain prior written authorization from patients, IRB boards, or other agreements that protect data and reidentification.	VA
129	Guideline for patient information management. In: Guidelines for Perioperative Practice. AORN Inc; 2026:379–416. doi: 10.6015/h7c9t5 [IVA]	Guideline	n/a	n/a	n/a	n/a	Guidance for required information and data privacy related to protected health information	IVA
130	Abid R, Hussein AA, Guru KA. Artificial intelligence in urology: current status and future perspectives. Urol Clin North Am. 2024;51(1):117–130. doi: 10.1016/j.ucl.2023.06.005 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	AI is used in urologic diagnostics, outcome prediction, and robotics, but obstacles to fully autonomous surgery remain. Progress depends on data collection, preparation, and annotation; AI must be interpretable to users and patients; and ethical concerns—racial bias, treatment implications, and consent—must be addressed.	VA
131	Farid Y, Chang C, Marcasciano M et al. Consent 2.0: informed choices in the age of artificial intelligence. Surgery. 2024;175(5):1454–1455. doi: 10.1016/j.surg.2023.12.027 [VB]	Expert Opinion	n/a	n/a	n/a	n/a	Patient consent is crucial for the responsible use of AI in health care. Ethical and accurate data collection empowers AI to produce better results, while safeguarding patient autonomy and privacy. The authors suggest that patients should be informed when AI is used during surgical procedures.	VB
132	Hermansen A, Regier DA, Pollard S. Developing data sharing models for health research with real-world data: a scoping review of patient and public preferences. J Med Syst. 2022;46(12):86. doi: 10.1007/s10916-022-01875-3 [VB]	Literature Review	n/a	n/a	n/a	n/a	Patients and the public hold specific, persistent, and sometimes conflicting preferences regarding control, consent, incentivization, and usability when researchers access their health data. Capturing these preferences is integral to designing successful, trusted data-sharing platforms, and trust in providers and systems affects willingness to share data and adopt new technology.	VB
133	45 CFR 164.514. Other requirements relating to uses and disclosures of protected health information. Code of Federal Regulations. Accessed April 8, 2026. https://www.ecfr.gov/current/title-45/subtitle-A/subchapter-C/part-164/subpart-E/section-164.514	Regulatory	n/a	n/a	n/a	n/a	Requirement for disclosures of PHI	n/a
134	Duffourc M, Gerke S. Generative AI in health care and liability risks for physicians and safety concerns for patients. JAMA[JAMA and JAMA Network Journals Full Text]. 2023;330(4):313–314. doi: 10.1001/jama.2023.9630 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	Physicians and patients should exercise caution when relying on AI-generated information due to potential liability risks and safety concerns. It's important to consider the liability implications of GenAI tools and safeguard patients from harmful treatments or recommendations	VA
135	McGreevey JD 3rd, Hanson CW 3rd, Koppel R. Clinical, legal, and ethical aspects of artificial intelligence–assisted conversational agents in health care. JAMA[JAMA and JAMA Network Journals Full Text]. 2020;324(6):552–553. doi: 10.1001/jama.2020.2724 [VB]	Expert Opinion	n/a	n/a	n/a	n/a	Conversational agents (CAs) may be effective in facilitating remote patient management, enabling clinicians to focus on other functions, and aiding data collection.	VB
136	Ghosh A, Kandasamy D. Interpretable artificial intelligence: why and when. AJR Am J Roentgenol. 2020;214(5):1137–1138. doi: 10.2214/AJR.19.22145 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	The authors conclude that AI opacity is a major barrier to clinical implementation. They urge research to go beyond reporting accuracy and sensitivity and instead explain the reasons behind predictions to enrich biological understanding and knowledge.	VA

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137	Görges M, Ansermino JM. Augmented intelligence in pediatric anesthesia and pediatric critical care. Curr Opin Anaesthesiol. 2020;33(3):404–410. doi: 10.1097/ACO.0000000000000845 [VB]	Expert Opinion	n/a	n/a	n/a	n/a	Augmented intelligence has the potential to improve patient outcomes, reduce costs, and improve clinician workflow in pediatric anesthesia and critical care. However, challenges such as implementation, external validation, user acceptance, ethics, and regulation must be addressed.	VB
138	Lazăr DC, Avram MF, Faur AC et al. The impact of artificial intelligence in the endoscopic assessment of premalignant and malignant esophageal lesions: present and future. Medicina (Kaunas). 2020;56(7):364. doi: 10.3390/medicina56070364 [VA]	Literature Review	n/a	n/a	n/a	n/a	Promising results show a good accuracy of Computer Assisted Diagnosis (CAD) algorithms associated with advanced endoscopic techniques for diagnosis of esophageal carcinomas in the early and endoscopic treatable stages, which is associated with improved quality of life and better survival.	VA
139	Le Berre C, Sandborn WJ, Aridhi S et al. Application of artificial intelligence to gastroenterology and hepatology. Gastroenterology. 2020;158(1):76–94. doi: 10.1053/j.gastro.2019.08.058 [VA]	Literature Review	n/a	n/a	n/a	n/a	AI has become an important part of gastroenterology and hepatology research. While AI shows promise in improving diagnostic accuracy and predicting treatment responses, future research should address the variability in performance metrics, lack of high-quality datasets, and ethical challenges.	VB
140	Lu YB, Lu SC, Huang YN et al. A novel convolutional neural network model as an alternative approach to bowel preparation evaluation before colonoscopy in the COVID-19 era: a multicenter, single-blinded, randomized study. Am J Gastroenterol. 2022;117(9):1437–1443. doi: 10.14309/ajg.0000000000001900 [IA]	RCT	1,434 patients undergoing colonoscopy	AI-CNN model used to evaluate the quality of bowel preparation n=730	The control group performed self-evaluation per routine practice n=704	Homogeneity between the results of the 2 methods. The secondary outcomes included the quality of bowel preparation according to the Boston Bowel Preparation Scale (BBPS), polyp detection rate, and adenoma detection rate.	The novel AI-CNN model demonstrated comparable outcomes to routine practice and may serve as an alternative approach for evaluating bowel preparation quality before colonoscopy.	IA
141	Maurer LR, Bertsimas D, Bouardi HT et al. Trauma outcome predictor: an artificial intelligence interactive smartphone tool to predict outcomes in trauma patients. J Trauma Acute Care Surg. 2021;91(1):93–99. doi: 10.1097/TA.0000000000003158 [IIIA]	Nonexperimental	934,053 patients were included (747,249 derivation; 186,804 validation)	Development and validation of OCT algorithms to predict in-hospital mortality and complications, Derivation cohort: n=747,249; Validation cohort: n= 186,804	n/a	Predicting in-hospital mortality and complications	Trauma Outcome Predictor (TOP) is suggested as an AI-based, interpretable, accurate, and nonlinear risk calculator for predicting outcome in trauma patients	IIIA
142	Wang E, Brenn BR, Matava CT. State of the art in clinical decision support applications in pediatric perioperative medicine. Curr Opin Anaesthesiol. 2020;33(3):388–394. doi: 10.1097/ACO.0000000000000850 [VB]	Literature Review	n/a	n/a	n/a	n/a	Clinical decision support systems in electronic health records can reduce morbidity from any disease by 10-18%.	VB
143	Zhao Y, Zheng S, Cai N et al. Utility of artificial intelligence for real-time anatomical landmark identification in ultrasound-guided thoracic paravertebral block. J Digit Imaging. 2023;36(5):2051–2059. doi: 10.1007/s10278-023-00851-8 [IIIA]	Nonexperimental	40 patients	Developed an artificial neural network (ANN) to automatically identify anatomical structures in ultrasound images	n/a	Intersection over Union (IoU) and Dice similarity coefficient (DSC or Dice coefficient) for PVS, lung, and bone; accuracy percentages	AI has good prospects for use in thoracic paravertebral block (TPVB), with the performance of the developed ANN being highly satisfactory.	IIIA
144	Zhou Z, Yang Z, Jiang S, Zhuo J, Zhu T, Ma S. Surgical navigation system for hypertensive intracerebral hemorrhage based on mixed reality. J Digit Imaging. 2022;35(6):1530–1543. doi: 10.1007/s10278-022-00676-x [VA]	Organizational Experience	10 patients	Multimodel mixed reality navigation system for HICH surgery	n/a	Mean registration error and average time consumption	The multimodel mixed reality navigation system for hypertensive intracerebral hemorrhage (HICH) surgery is sufficiently accurate and effective for clinical application.	VA
145	Rajjoub R, Arroyave JS, Zaidat B et al. ChatGPT and its role in the decision-making for the diagnosis and treatment of lumbar spinal stenosis: a comparative analysis and narrative review. Global Spine J. 2024;14(3):998–1017. doi: 10.1177/21925682231195783 [IIIC]	Nonexperimental	14 questions	Prompted ChatGPT with 14 questions proposed by the North American Spine Society	n/a	Accuracy and similarity of ChatGPT's responses to current literature and NASS guidelines	ChatGPT has the potential to support the decision-making process for lumbar spinal stenosis (LSS) diagnosis and treatment, but further research is needed to validate its use in the clinical space	IIIC
146	Kenig N, Monton Echeverria J, De la Ossa L. Identification of key breast features using a neural network: applications of machine learning in the clinical setting of plastic surgery. Plast Reconstr Surg. 2024;153(2):273e–280e. doi: 10.1097/PRS.0000000000010603 [IIIB]	Nonexperimental	200 training images and 47 test images of patients who underwent breast surgery	Ad hoc convolutional neural network identification of breast features	n/a	Detection of key breast features (boundaries of the breast, nipple-areola complex, and suprasternal notch)	An ad hoc neural network localized key breast features with a 97.74% detection rate. Neural networks and machine learning could improve breast-symmetry evaluation in plastic surgery through automated, rapid feature detection, but further study and development are needed.	IIIB

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147	Iftikhar M, Saqib M, Zareen M, Mumtaz H. Artificial intelligence: revolutionizing robotic surgery: review. Ann Med Surg (Lond). 2024;86(9):5401–5409. doi: 10.1097/MS9.0000000000002426 [VB]	Literature Review	n/a	n/a	n/a	n/a	AI integration holds promise for advancing surgical care, with potential benefits including improved outcomes and broader access to specialized expertise. Advantages include enhanced precision and accuracy, reduced fatigue, and improved safety; limitations include high development and implementation costs, the need for high-quality training data, and data security. Addressing these challenges and promoting responsible adoption are essential.	VB
148	Giordano C, Brennan M, Mohamed B, Rashidi P, Modave F, Tighe P. Accessing artificial intelligence for clinical decision-making. Front Digit Health. 2021;3:645232. doi: 10.3389/fdgth.2021.645232 [VA]	Literature Review	n/a	n/a	n/a	n/a	Areas of use for health AI include risk stratification, patient outcome optimization, early warning of acute decompensation, and mitigation of bias.	VA
149	Loftus TJ, Vlaar APJ, Hung AJ et al. Executive summary of the artificial intelligence in surgery series. Surgery. 2022;171(5):1435–1439. doi: 10.1016/j.surg.2021.10.047 [VA]	Literature Review	n/a	n/a	n/a	n/a	Emerging evidence suggests AI can augment surgeons through decision support, technical-skill assessment, and semi-autonomous tasks ranging from patching foregut defects to optimizing regional resource allocation. Substantial challenges remain, but recent progress in achieving AI performance advantages in surgery suggests these challenges can and will be overcome.	VA
150	Farrow L, Zhong M, Anderson L. Use of natural language processing techniques to predict patient selection for total hip and knee arthroplasty from radiology reports. Bone Joint J. 2024;106-B(7):688–695. doi: 10.1302/0301-620X.106B7.BJJ-2024-0136 [IIIA]	Nonexperimental	THA: 5,558 patient radiology reports, TKA: 7,457 patient radiology reports	NLP algorithm	ground truth data; surgery or no surgery	accuracy, F1 score, and area under the receiver operating curve (AUROC) to predict patient selection for THA and TKA.	Routine preoperative radiology reports show promise for screening THA candidates, but not TKA. Further model testing and training are needed for new cohorts, and documentation variability across facilities and regions should be considered before deploying AI-based tools.	IIIA
151	Yang WF, Su YX. Artificial intelligence-enabled automatic segmentation of skull CT facilitates computer-assisted craniomaxillofacial surgery. Oral Oncol. 2021;118:105360. doi: 10.1016/j.oraloncology.2021.105360 [VA]	Case Report	Three patients enrolled in a clinical trial of computer-assisted craniomaxillofacial surgery	AI-enabled automatic segmentation in Mimics Viewer	n/a	The performance of AI segmentation was evaluated based on the requirements of computer-assisted surgery	The AI-enabled automatic segmentation could facilitate the preoperative virtual planning and postoperative outcome verification, enhancing the workflow of computer-assisted surgery.	VA
152	Zaver HB, Mzaik O, Thomas J et al. Utility of an artificial intelligence enabled electrocardiogram for risk assessment in liver transplant candidates. Dig Dis Sci. 2023;68(6):2379–2388. doi: 10.1007/s10620-023-07928-y [IIIA]	Nonexperimental	Cohort A = transplant recipient cohort comprised of 300 consecutive patients undergoing LT over a 2-year period. Cohort B = 412 patients who underwent pre-LT evaluation.	AI-ECG analysis	n/a	Predicted cardiac factors (ie, asymptomatic left ventricular systolic dysfunction, potential for developing post-operative atrial fibrillation	A positive AI-ECG screen for low EF or atrial fibrillation can flag risk of post-operative cardiac dysfunction or predict new-onset AF after liver transplant. AI-ECG is a useful, readily implemented adjunct in transplant evaluation.	IIIA
153	Allou N, Allyn J, Provenchere S et al. Clinical utility of a deep-learning mortality prediction model for cardiac surgery decision making. J Thorac Cardiovasc Surg. 2023;166(6):e567–e578. doi: 10.1016/j.jtcvs.2023.01.022 [IIIA]	Nonexperimental	165,640 patients who underwent cardiac surgery	Deep-learning mortality prediction model	EuroSCORE II and two machine-learning models	Predictive accuracy and clinical utility in cardiac surgery decision making	The deep-learning model showed better predictive accuracy and greater clinical utility than EuroSCORE II and two machine-learning models, suggesting it could become the gold standard for cardiac surgery decision-making. Additional research, including RCTs, is needed.	IIIA
154	Wissel BD, Greiner HM, Glauser TA et al. Automated, machine learning–based alerts increase epilepsy surgery referrals: a randomized controlled trial. Epilepsia. 2023;64(7):1791–1799. doi: 10.1111/epi.17629 [IA]	RCT	4858 children with epilepsy and 284 identified as potential surgical candidates	204 patients received an alert for a neurosurgical evaluation	96 patients received standard care	Referral for a neurosurgical evaluation	Machine learning– based automated alerts may improve the utilization of referrals for epilepsy surgery evaluations	IA
155	Ramamurthi A, Neupane B, Deshpande P et al. Development and validation of an artificial intelligence system for surgical case length prediction. Surgery. 2025;179:108942. doi: 10.1016/j.surg.2024.09.051 [IIIA]	Nonexperimental	Total of 125,493 inpatient, elective surgical cases longer than 30 minutes	Artificial intelligence model for surgical case length prediction	Existing electronic health record predictions	Predicted surgical case length in minutes	An artificial intelligence model for surgical case length estimation outperforms existing institutional electronic health record predictions.	IIIA
156	Yahagi M, Hiruta R, Miyauchi C, Tanaka S, Taguchi A, Yaguchi Y. Comparison of conventional anesthesia nurse education and an artificial intelligence chatbot (ChatGPT) intervention on preoperative anxiety: a randomized controlled trial. J Perianesth Nurs. 2024;39(5):767–771. doi: 10.1016/j.jopan.2023.12.005 [IA]	RCT	100 adult patients	Intervention group of 50 patients interacted with ChatGPT	Control group of 50 patients received standard preoperative information from anesthesia nurses	Reduction in preoperative anxiety measured by the Japanese State-Trait Anxiety Inventory (STAI) self-report questionnaire	The ChatGPT intervention significantly reduced preoperative anxiety compared with the control group; however, no overall difference in the STAI scores was observed.	IA

REFERENCE #	CITATION	EVIDENCE TYPE	SAMPLE SIZE/ POPULATION	INTERVENTION(S)	CONTROL/ COMPARISON	OUTCOME MEASURE(S)	CONCLUSION(S)	CONSENSUS
157	Miller CA, Locke RA, Holck HW et al. Evaluation of a novel augmented reality educational tool and its effects on patient experience: a randomized controlled trial. Indian J Urol. 2024;40(1):25–30. doi: 10.4103/iju.iju_191_23 [IB]	RCT	100 patients with initial diagnoses of kidney masses or stones	Education using AR software on a tablet	Patients educated through traditional discussion, imaging, and hand-drawn illustrations	Patient understanding and satisfaction evaluated through pre- and post-physician encounter surveys	AR did not significantly increase self-reported patient understanding but suggested as a potential avenue to increase patient satisfaction with educational tools used during consultations	IB
158	El Hechi MW, Maurer LR, Levine J et al. Validation of the artificial intelligence–based Predictive Optimal Trees in Emergency Surgery Risk (POTTER) Calculator in emergency general surgery and emergency laparotomy patients. J Am Coll Surg. 2021;232(6):912–919. doi: 10.1016/j.jamcollsurg.2021.02.009 [IIIA]	Nonexperimental	59,955 patients; subgroup 18,925 patients who underwent Emergency General Surgery (EGS) and Emergency Laparotomy (EL)	POTTER prediction tool	Ground truth patient outcomes	POTTER prediction of 30-day postoperative mortality, morbidity, and 18 specific complications	POTTER is an interpretable, accurate, and user-friendly predictor of 30-day outcomes in patients undergoing EGS and EL. POTTER could prove useful for bedside counseling of patients and their families and for benchmarking of EGS care.	IIIA
159	El Moheb M, Gebran A, Maurer LR et al. Artificial intelligence versus surgeon gestalt in predicting risk of emergency general surgery. J Trauma Acute Care Surg. 2023;95(4):565–572. doi: 10.1097/TA.0000000000004030 [IIB]	Quasi-experimental	30 surgeons	15 surgeons predicting outcomes with access to POTTER	15 surgeons predicting outcomes without access to POTTER	Predictive performance of mortality, septic shock, ventilator dependence, bleeding, and pneumonia	The AI risk calculator POTTER outperformed surgeons in predicting the postoperative mortality and outcomes of EGS patients, and when used, improved the individual surgeons' risk prediction.	IIB
160	Maurer LR, Chetlur P, Zhuo D et al. Validation of the AI-based Predictive OpTimal Trees in Emergency Surgery Risk (POTTER) calculator in patients 65 years and older. Ann Surg. 2023;277(1):e8–e15. doi: 10.1097/SLA.0000000000004714 [IIIA]	Nonexperimental	29,366 patients	POTTER tool	n/a	30-day mortality and postoperative complications	POTTER is an interpretable and highly accurate predictor of in-hospital mortality in elderly ES patients up to age 85 years. POTTER could prove useful for bedside counseling and for benchmarking of ES care.	IIIA
161	Kovoor JG, Bacchi S, Gupta AK et al. Surgery's Rosetta Stone: natural language processing to predict discharge and readmission after general surgery. Surgery. 2023;174(6):1309–1314. doi: 10.1016/j.surg.2023.08.021 [IIIA]	Nonexperimental	12,457 patients.	NLP models	n/a	Accuracy of natural language processing models in predicting discharge within 48 hours and 7 days, and readmission within 30 days.	Modern NLP models, particularly BERT, can accurately identify general surgery patients who will be discharged within 48 hours, but are less able to identify those discharged within 7 days or readmitted within 30 days. Assessing the clinical relevance of these findings is essential to realize the model's maximal benefit.	IIIA
162	Datta S, Loftus TJ, Ruppert MM et al. Added value of intraoperative data for predicting postoperative complications: The MySurgeryRisk PostOp Extension. J Surg Res. 2020;254:350–363. doi: 10.1016/j.jss.2020.05.007 [IIIA]	Nonexperimental	11,969 surgeries	Postoperative complication risk AI calculator (preop and intraop data)	Postoperative complication risk AI calculator (preop data only)	Accuracy, discrimination, and precision in predicting postoperative complications.	Incorporating intraoperative physiological data improved the predictive accuracy, discrimination, and precision for postoperative complications. However, it is unknown whether better predictions translate to better clincial decisions and outcomes.	IIIA
163	Guideline for medication safety. In: Guidelines for Perioperative Practice. AORN Inc; 2026:501–554. doi: 10.6015/a2j6j8 [IVA]	Guideline	n/a	n/a	n/a	n/a	Guidance for medication safety practices	IVA
164	Lonsdale H, Gray GM, Ahumada LM, Matava CT. Machine vision and image analysis in anesthesia: narrative review and future prospects. Anesth Analg. 2023;137(4):830–840. doi: 10.1213/ANE.0000000000006679 [VA]	Literature Review	n/a	n/a	n/a	n/a	Machine vision's performance and uses in anesthesia will grow as underlying algorithms advance outside medicine. Anesthesiologists must be prepared to confidently assess which devices are safe, appropriate, and add value to patient care.	VA
165	Xia M, Jin C, Zheng Y et al. Deep learning–based facial analysis for predicting difficult videolaryngoscopy: a feasibility study. Anaesthesia. 2024;79(4):399–409. doi: 10.1111/anae.16194 [IIA]	Quasi-experimental	5849 patients	ResNet-18 neural network model for predicting difficult videolaryngoscopy	5335 non-difficult videolaryngoscopy patients	Predictive performance of AI model compared to traditional methods	Artificial intelligence-based facial analysis is a feasible technique for predicting difficulty during videolaryngoscopy, and the model developed using neural networks has higher predictive performance than traditional methods.	IIA
166	Harish V, Morgado F, Stern AD, Das S. Artificial intelligence and clinical decision making: the new nature of medical uncertainty. Acad Med. 2021;96(1):31–36. doi: 10.1097/ACM.0000000000003707 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	AI systems offer an opportunity to refine the medical diagnostic process but integration as an integral part of the clinical decision-making framework requires acceptance of relative uncertainty as a fundamental aspect.	VA
167	Zhang K, Khosravi B, Vahdati S, Erickson BJ. FDA review of radiologic AI algorithms: process and challenges. Radiology. 2024;310(1):e230242. doi: 10.1148/radiol.230242 [VA]	Case Report	n/a	n/a	n/a	n/a	The FDA-cleared AI triage tool misdiagnosed an intracranial hemorrhage, which was later corrected to a chronic ischemic stroke by human review, emphasizing the importance of human-machine interaction and ongoing postmarket surveillance.	VA
168	Hardy M, Harvey H. Artificial intelligence in diagnostic imaging: impact on the radiography profession. Br J Radiol. 2020;93(1108):20190840. doi: 10.1259/bjr.20190840 [VA]	Expert Opinion	n/a	n/a	n/a	n/a	The radiography profession must remain engaged and involved in the successful delivery and implementation of AI systems. Implementation of health AI will have effects on the workflow and responsibilities of health care workers and these should be addressed and managed early to foster adoption.	VA

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169	21 CFR 56.111. Criteria for IRB approval of research. Code of Federal Regulations. Accessed April 8, 2026. https://www.ecfr.gov/current/title-21/chapter-I/subchapter-A/part-56/subpart-C/section-56.111	Regulatory	n/a	n/a	n/a	n/a	Requirements for IRB ethics boards	n/a
170	Russell RG, Lovett Novak L, Patel M et al. Competencies for the use of artificial intelligence–based tools by health care professionals. Acad Med. 2023;98(3):348–356. doi: 10.1097/ACM.0000000000004963 [IIIB]	Qualitative	15 experts in AI-based tools in the health care setting	n/a	n/a	Competencies needed for the use of AI-based tools by health care professionals	The development of ethically competent individuals and organizations is critical if the potential benefits of AI-based tools are to be maximized and their potential harms diminished.	IIIB
171	Ethics and Governance of Artificial Intelligence for Health: Guidance on Large Multi-modal Models. World Health Organization; 2024. Accessed April 8, 2026. https://www.who.int/publications/i/item/9789240084759 [IVB]	Consensus	n/a	n/a	n/a	n/a	Potential benefits and risks should be evaluated when developing and deploying large multimodal models (LMMs) in healthcare. Although LMMs are relatively new, their rapid uptake led WHO to issue this guidance to support safe, successful, and sustainable worldwide use.	IVA
172	Patino GA, Amiel JM, Brown M, Lypson ML, Chan TM. The promise and perils of artificial intelligence in health professions education practice and scholarship. Acad Med. 2024;99(5):477–481. doi: 10.1097/ACM.0000000000005636 [VB]	Expert Opinion	n/a	n/a	n/a	n/a	AI should be seen as a tool that complements faculty and researcher skills, while high-stakes decisions in health professions education remain a human responsibility. Training students, faculty, and scholars on appropriate use is among the most immediate needs and a promising research avenue. Bias detection and monitoring—during both development and application—should be a key training component.	VB
173	Kucukkaya A, Arikan E, Goktas P. Unlocking ChatGPT's potential and challenges in intensive care nursing education and practice: a systematic review with narrative synthesis. Nurs Outlook. 2024;72(6):102287. doi: 10.1016/j.outlook.2024.102287 [IIIA]	Systematic Review	5 studies; 2023-2024	n/a	n/a	n/a	ChatGPT offers promising ICU benefits but requires careful management. Ongoing research and adherence to ethical standards are essential, and integration should include continuous clinician training on using AI as a supplement without undermining expertise.	IIIA