INTERNATIONAL JOURNAL OF NEXT-GENERATION ENGINEERING AND TECHNOLOGY (IJNGET)

eISSN: 3087-4319

Volume. 03, Issue. 02, pp. 21-31, February 2026

QUANTITATIVE EVALUATION OF ARTIFICIAL INTELLIGENCE IN HOSPITAL MANAGEMENT: SYSTEMATIC REVIEW OF REAL-WORLD IMPLEMENTATIONS AND OUTCOMES (2019–2024)

Jean Paul Kazungu[1], Jean Pierre Ntayagabiri[2], Jeremie Ndikumagenge[3], M. Kokou Assogba[4]

[1]Doctoral School of the University of Burundi, Center for Research in Infrastructure, Environment and Technology (CRIET), Burundi

[2]Department of Information and Communication Technologies, Higher Institute of Applied Sciences, University of Burundi, Burundi

[3]Institute of Digital Technologies, University of Burundi, Burundi

[4]EPAC, Ecole Polytechnique d'Abomey-Calavi; Université d'Abomey-Calavi, Cotonou-Bénin

Article received: 27/11/2025, Article Accepted: 02/12/2025, Article Published: 26/02/2026

DOI: - https://doi.org/10.55640/ijnget-v03i02-04

ABSTRACT

Hospitals around the world are under growing pressure due to limited resources, shifting demographics, and rising demands for quality care. Artificial intelligence (AI) has emerged as a promising ally to help address these challenges, yet real-world evidence about its implementation and impact remains scattered. This study, conducted following PRISMA 2020 guidelines, reviewed 52 empirical investigations published between 2019 and 2024 that reported quantitative outcomes of AI applications in hospital management. Our findings show that AI adoption rose from 66% in 2023 to 71% in 2024, although sharp disparities persist between university hospitals (87%) and rural facilities (41%). Meta-analyses revealed significant benefits: administrative efficiency improved by 30–45%, diagnostic accuracy by 12–18%, hospital stays shortened by 1.2–2.1 days, and resource allocation costs dropped by 15–25%. Despite initial investments ranging from $430,000 to $6.2 million, the average return on investment reached 267% within three years. However, implementation remains challenging—77% of projects faced technical integration issues, 71% reported inadequate staff training, and 56% struggled with regulatory compliance. Overall, while AI brings measurable and meaningful gains to hospital management, its success depends as much on human and organizational readiness as on technological capability. Bridging the equity gap between well-resourced and under-resourced institutions should be a policy priority, and future research must focus on long-term sustainability, standardized evaluation frameworks, and strategies adapted to resource-limited settings.

Keywords: Artificial Intelligence, Hospital Management, Healthcare Administration, Clinical Decision Support, Digital Health.

1. INTRODUCTION

Healthcare delivery has become increasingly complex over the past decade. Hospitals today must balance limited resources against rising patient volumes, manage aging populations with multiple chronic conditions, and meet ever-higher expectations for quality and safety—all while maintaining financial sustainability [1–3]. Traditional management approaches, grounded largely in human experience and intuition, are often insufficient to handle such systemic pressures [4, 5].

Artificial intelligence (AI) offers a transformative way forward. Through machine learning, hospitals can detect subtle patterns in massive datasets; natural language processing enables the extraction of insights from unstructured clinical notes; and predictive analytics can anticipate patient flow or resource needs with remarkable accuracy [6–9]. Yet, until recently, most AI applications remained confined to controlled research environments or small-scale pilot programs, limiting their real-world impact.

The COVID-19 pandemic marked a turning point. Hospitals that had already deployed AI-driven systems were able to adapt more quickly to surging patient demand, evolving treatment protocols, and volatile supply chains [10–12]. In many of these institutions, AI tools contributed to better resource utilization, improved decision-making, and, in some cases, enhanced patient outcomes during the crisis [13–15]. This experience profoundly reshaped how healthcare leaders view digital transformation, accelerating investment in AI technologies and compressing adoption timelines [16, 17].

Despite this growing enthusiasm, fundamental questions remain. Many studies still examine isolated applications—a scheduling algorithm here, a diagnostic model there—without capturing the broader patterns and implications of AI implementation in hospital ecosystems [18–20]. A significant proportion of publications also lack methodological rigor, often relying on vendor-reported results or single-site case studies [21–23]. As a result, important gaps persist regarding cost-effectiveness at scale, long-term sustainability once initial enthusiasm wanes, equity implications for under-resourced facilities, and the organizational factors that distinguish success from failure [24–26].

To address these gaps, this systematic review synthesizes quantitative evidence from real-world implementations of AI in hospital management. Specifically, it seeks to answer five key questions:

What are the current patterns of AI adoption across hospital types and geographic regions?

What measurable outcomes have been achieved in both operational and clinical domains?

What barriers consistently arise during implementation, and what factors predict success?

How cost-effective is AI integration, and what return on investment does it yield?

What future research priorities and policy directions can support sustainable and equitable AI deployment?

By applying rigorous PRISMA 2020 methodology to analyze 52 high-quality studies, this review aims to provide hospital administrators, clinicians, and policymakers with actionable, evidence-based insights to guide effective AI implementation and strategic decision-making in healthcare.

2. METHODS

2.1 Study Design and Search Strategy

This systematic review was conducted in full accordance with the PRISMA 2020 guidelines [27]. We systematically searched six major electronic databases—PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and the Cochrane Library—for studies published between January 1, 2019, and December 31, 2024. The year 2019 was chosen as the starting point because it marked a pivotal moment when artificial intelligence (AI) in hospital management began shifting from experimental research toward operational deployment in real-world healthcare systems. The search strategy combined three conceptual domains—AI technologies, hospital management, and implementation—using a mix of MeSH terms and free-text keywords. Terms related to AI included artificial intelligence, machine learning, deep learning, neural networks, natural language processing, predictive analytics, computer vision, and expert systems. For hospital management, we incorporated expressions such as hospital operations, clinical workflow, resource allocation, capacity management, and quality improvement. The third domain, implementation, captured terms like adoption, integration, deployment, evaluation, and impact assessment. Search strings were optimized for each database's indexing system—using MeSH headings in PubMed, for instance, and keyword-focused strategies in IEEE Xplore. To ensure completeness, we also manually screened the reference lists of included papers and relevant reviews for additional eligible studies.

2.2 Eligibility Criteria

Studies were considered eligible if they met five main conditions: they had to be published in a peer-reviewed journal between 2019 and 2024; report real-world implementations of AI within hospital management contexts rather than theoretical models; provide quantitative outcome data; be written in English, French, or Spanish; and include either at least 100 patients or one year of institutional data. Eligible designs encompassed randomized controlled trials, quasi-experimental and cohort studies, cross-sectional analyses, and rigorous before–after case studies. We excluded publications that were purely theoretical or simulated, conference abstracts, editorials, and commentaries lacking full methodology, as well as studies reporting duplicate datasets from the same institution. Articles focusing on AI applications unrelated to hospital management, such as drug discovery or genomic research, were also omitted.

2.3 Study Selection

The selection process was managed using Covidence software. Two reviewers independently screened all titles and abstracts according to the predefined inclusion criteria. Disagreements were resolved through discussion, and when consensus could not be reached, a third senior reviewer adjudicated the decision. All studies passing initial screening underwent full-text review under the same procedure. Inter-reviewer reliability was high (Cohen's $\kappa = 0.87$), reflecting strong consistency between evaluators.

2.4 Data Extraction

Before formal data extraction, we developed and pilot-tested standardized extraction forms to ensure consistency across reviewers. For each included study, two reviewers independently captured detailed information about study design, setting, geographic location, sample size, and study period. They also recorded specifics of the AI system used, including algorithm type, integration approach, and vendor characteristics, as well as all reported outcomes—ranging from administrative efficiency and clinical performance to cost metrics and user satisfaction. Implementation-related variables, such as technical barriers, facilitating factors, training initiatives, and support mechanisms, were also extracted. Quality indicators, including funding source and potential conflicts of interest, were noted. When data were incomplete or unclear, authors were contacted directly. Of the 33 corresponding authors reached, 22 (67%) provided additional clarifications or datasets, which were integrated into the final analysis.

2.5 Quality Assessment

Study quality was assessed independently by two reviewers using validated tools appropriate for each study design. We applied the Cochrane Risk of Bias 2 (RoB 2) tool for randomized controlled trials [28], ROBINS-I for non-randomized intervention studies [29], and a modified Newcastle–Ottawa Scale (NOS) for observational studies [30]. Each assessment evaluated potential sources of bias, including selection, performance, detection, attrition, reporting, and confounding. Based on these evaluations, studies were classified as having low, moderate, or high overall risk of bias. These classifications subsequently informed the sensitivity analyses, allowing us to assess the robustness of pooled results by excluding studies deemed high-risk.

2.6 Data Synthesis and Statistical Analysis

We conducted an initial narrative synthesis of the findings in accordance with the SWiM (Synthesis Without Meta-analysis) framework [31]. When multiple studies reported comparable quantitative outcomes with acceptable homogeneity, we proceeded with random-effects meta-analyses using Review Manager version 5.4 [32]. Statistical heterogeneity was quantified through I^2 and τ^2 statistics. Effect sizes were expressed as standardized mean differences (SMDs) for continuous variables and risk ratios (RRs) for categorical outcomes, both reported with 95% confidence intervals (CIs). We conducted subgroup analyses to explore sources of variability related to hospital type (academic versus community), geographic region (North America, Europe, Asia, and other regions), AI application domain (administrative versus clinical), and implementation maturity (pilot projects versus full-scale deployments). Sensitivity analyses were used to test the stability of results by excluding studies with high risk of bias. Potential publication bias was examined through funnel plot asymmetry and Egger's regression test, while meta-regression analyses investigated the relationship between implementation characteristics and outcome magnitude. All statistical tests were two-tailed, and a p-value below 0.05 was considered statistically significant.

3. RESULTS

A total of 52 studies met our inclusion criteria, encompassing over 1.2 million patient encounters and spanning 23 countries. Research was concentrated in North America (38%) and Europe (33%), followed by Asia (21%) and Africa (8%). The majority of studies (61%) were conducted in tertiary academic hospitals, with the remainder in community, specialty, or private healthcare settings. This distribution reflects both greater research capacity and resource availability in larger institutions.

As summarized in Table 1, studies varied in regional distribution, primary AI application domains, and the types of algorithms employed. Machine learning models were most common (68%), while natural language processing (NLP) and deep learning were frequently applied in diagnostic applications, particularly in radiology and pathology.

Table 1. Overview of Included Studies

Region	Number of Studies (%)	Primary AI Application	Common Algorithms Used
North America	20 (38%)	Resource allocation, triage	ML, NLP, predictive analytics

Europe	17 (33%)	Clinical decision support	Deep learning, logistic models
Asia	11 (21%)	Imaging and diagnostics	CNN, ensemble methods
Africa	4 (8%)	Operational optimization	Random forest, ANN

3.1 Patterns of AI Adoption

AI adoption has accelerated markedly in recent years. Surveys suggest that implementation rates increased from 66% in 2023 to 71% in 2024, with university medical centers achieving the highest adoption (87%) and rural hospitals the lowest (41%). These differences highlight a persistent digital divide, with smaller or under-resourced facilities hindered by limited IT infrastructure, capital constraints, and smaller patient volumes.

AI implementations clustered across four domains: administrative automation, clinical decision support, resource optimization, and patient flow management. Most hospitals deployed AI in multiple domains, with a median of 2.4 applications per institution. This distribution and adoption pattern is summarized in Table 2, which also highlights domain-specific adoption rates.

Table 2. AI Adoption by Application Domain

Application Domain	Number of Studies	Adoption (%)
Administrative automation	38	73%
Clinical decision support	32	62%
Resource optimization	30	58%
Patient flow management	28	54%

3.2 Operational Efficiency

Across 36 studies examining workflow and administrative outcomes, AI consistently streamlined processes and optimized resource allocation. Appointment scheduling delays decreased by an average of 27%, and predictive bed management improved turnover rates by 19%, enabling hospitals to respond more effectively during peak demand. These improvements are synthesized in Table 3, showing the mean improvements and variability across studies.

Table 3. AI Impact on Operational Metrics

Metric Evaluated	Mean Improvement	Range Across Studies	Evidence Quality
Appointment scheduling delays	–27%	–12% to –41%	High
Bed turnover time	+19%	+8% to +30%	Moderate
Resource utilization efficiency	+22%	+10% to +35%	High
Patient waiting time	–18%	–5% to –29%	High

3.3 Clinical Decision Support and Outcomes

Twenty-one studies evaluated AI-assisted clinical decision-making, including diagnostic support, early warning systems, and medication safety.

Diagnostic accuracy improved by 8–12%, with radiology and pathology experiencing the largest gains. Length of stay was reduced by 1.2–2.1 days on average.

Readmission rates fell by 4–7% in hospitals integrating predictive analytics into care pathways.

These results are summarized in Table 4, which presents the pooled clinical improvements across domains.

Table 4. AI Impact on Clinical Outcomes

Outcome	Mean Improvement	Range Across Studies	Evidence Quality
Diagnostic accuracy	+14.7%	+12.3% to +17.1%	High
Length of stay	–1.6 days	–1.2 to –2.1 days	Moderate
Readmission rates	–5%	–4% to –7%	Moderate
Adverse drug events	–22%	–15% to –30%	Moderate

3.4 Patient Flow and Capacity Management

AI-enabled triage systems and predictive models led to significant improvements in emergency department efficiency. Waiting times dropped by 19%, and throughput increased by 24%, particularly during high-volume periods. Bed management systems optimized discharges, reducing bottlenecks and enabling more coordinated care planning. Table 5 summarizes these key patient flow outcomes.

Table 5. AI Impact on Patient Flow and Capacity

Metric Evaluated	Mean Improvement	Range Across Studies	Evidence Quality
Emergency department waiting time	–19%	–5% to –29%	High
ED throughput	+24%	+15% to +32%	High
Hospital length of stay	–1.6 days	–1.2 to –2.1 days	Moderate
Bed utilization	+21%	+17% to +25%	Moderate

3.5 Economic Impact

Cost analyses from 19 studies revealed that initial investments ranged from $430,000 to $6.2 million, depending on scope and complexity. The pooled return on investment (ROI) averaged 267% over three years, with payback periods as short as 22 months. Administrative AI generated savings primarily through labor efficiency and reduced billing errors, whereas clinical AI delivered value through shorter stays, fewer complications, and enhanced throughput.

3.6 Implementation Barriers

Despite measurable benefits, challenges remain:

Technical: 77% faced data integration difficulties; 68% encountered interoperability issues.

Organizational: 64% reported staff resistance; 71% highlighted inadequate training.

Regulatory/Ethical: 56% struggled with compliance and algorithmic bias.

3.7 Key Success Factors

Successful AI deployment was rarely about technology alone. Executive sponsorship, pilot testing, hands-on training, and ongoing technical support emerged as critical determinants of success. Institutions that invested in organizational change management alongside technology consistently achieved superior outcomes.

4. DISCUSSION

4.1 Principal Findings

This systematic review synthesized evidence from 52 high-quality studies spanning six years of AI implementation in hospital management. Three key findings emerge.

First, AI adoption is accelerating but inequitably distributed. While overall implementation rates increased from 66% to 71% annually, the 46-percentage-point gap between university hospitals (87%) and rural hospitals (41%) represents more than a statistical disparity—it signals a widening digital divide that threatens to exacerbate existing healthcare inequities. Under-resourced facilities face compounding barriers: insufficient IT infrastructure, limited capital for investment, and smaller patient volumes that make per-patient costs less favorable.

Second, AI demonstrably improves both operational efficiency and clinical outcomes when properly implemented. Administrative efficiency gains of 30-45%, diagnostic accuracy improvements of 12-18%, and length-of-stay reductions averaging 1.6 days translate to meaningful benefits for patients and organizations. The 267% three-year ROI, while impressive, should be interpreted cautiously given methodological variations and potential publication bias toward positive results.

Third, successful implementation requires far more than purchasing software. The 77% of projects encountering data integration challenges, 71% facing training issues, and 64% experiencing staff resistance underscore that AI implementation is fundamentally an organizational transformation, not merely a technology deployment. The facilities that succeeded treated it as such—investing heavily in change management, user engagement, and workflow redesign.

4.2 Comparison with Existing Literature

Our findings align with recent systematic reviews demonstrating AI's potential in healthcare [33-37], while extending them in important ways. Previous reviews focused primarily on clinical applications like diagnostic imaging or drug dosing, giving less attention to operational and administrative domains. By examining hospital management broadly, we document AI's impact across the full spectrum of healthcare delivery.

Our 66-71% adoption rate substantially exceeds earlier estimates. A 2018 survey reported only 38% of hospitals using any AI [38], while a 2020 study found 54% adoption [39]. This acceleration likely reflects several factors: pandemic-driven digital transformation, improving AI technology maturity, and growing vendor ecosystems that reduce implementation barriers.

Our economic findings align with broader health IT literature showing favorable returns on technology investment [40, 41]. However, our more granular analysis reveals important nuances. Single-application deployments show faster payback but lower total returns than enterprise-wide implementations, helping administrators make more informed investment decisions.

The implementation barriers we identified—integration complexity, interoperability limitations, training needs—echo challenges documented across digital health innovations [42, 43]. This consistency suggests that addressing these barriers requires systemic solutions, not just AI-specific fixes. Healthcare organizations need better IT infrastructure, more robust data governance, and stronger implementation science capacity.

4.3 Practical Implications

For healthcare administrators: Our findings offer several actionable insights. First, resist vendor promises of "plug-and-play" solutions. Budget 2-3 times the software cost for integration, training, and workflow redesign. Second, don't underestimate change management. Allocate substantial resources to stakeholder engagement, communication, and addressing staff concerns. Third, start with targeted pilots rather than enterprise-wide deployments. Pilots allow learning and refinement while limiting downside risk.

Technology selection deserves careful attention. Demand evidence of real-world performance, not just vendor-provided metrics. Conduct thorough reference checks with comparable organizations. Ensure vendor contracts include performance guarantees and clear accountability for integration support.

For policymakers: The equity gap demands intervention. Rural and under-resourced hospitals need targeted support to avoid falling further behind. Possible approaches include:

Infrastructure grants specifically for IT modernization in underserved areas

Shared services models where multiple small hospitals pool resources

Technical assistance programs providing implementation guidance

Regulatory reforms that reduce compliance burdens for smaller organizations

Reimbursement policies should recognize and reward quality improvements from AI implementation, creating financial incentives for adoption. Current payment models often don't capture AI-generated value, particularly preventive benefits like reduced complications.

Regulatory clarity would accelerate adoption. Current uncertainty about liability, data governance, and approval requirements creates hesitation. Clear, reasonable regulatory frameworks—informed by implementation science rather than theoretical concerns—would help.

4.4 Future Directions

Although the evidence base is growing, several important gaps remain that future research should address.

Emerging technologies: Large language models like GPT-4 show real potential for clinical documentation, patient communication, and decision support. Early implementations suggest they could significantly reduce administrative burden, a major source of clinician burnout. However, concerns about accuracy, bias, and proper oversight remain, and these issues must be carefully studied before widespread deployment.

Federated learning offers a promising solution to data-sharing challenges. By training algorithms across multiple institutions without centralizing the data, federated approaches could improve model performance while protecting privacy. This is particularly relevant for rare diseases, where no single institution has enough data to develop robust models.

Integration with IoT sensors and wearable devices opens opportunities for continuous patient monitoring outside the hospital. These systems could allow earlier interventions and reduce readmissions, though they also raise challenges such as information overload and alert fatigue.

Key research gaps: Several priorities emerge from our analysis:

Long-term sustainability: Current studies typically follow outcomes for only 18 months. Do AI benefits persist over time, or do they fade once the novelty wears off? Are algorithms maintained and updated, or do they become obsolete? Studies with five-year follow-ups are needed.

Comparative effectiveness: Which AI approaches work best for which applications and settings? Direct comparisons are rare, yet they are essential for helping administrators choose between competing solutions.

Equity-focused research: Implementation strategies tailored to under-resourced hospitals are crucial. How can AI be made feasible for rural or safety-net institutions? How can it reduce, rather than worsen, healthcare disparities?

Standardized evaluation frameworks: The diversity of outcome measures and evaluation methods complicates evidence synthesis. There is a need for consensus metrics to assess AI implementation success across technical, clinical, operational, and financial dimensions.

Implementation science: Understanding not only whether AI works but also how to make it work consistently across diverse contexts is critical. Which organizational factors predict success? How can common barriers be overcome? What strategies prove most effective?

4.5 Limitations

Several limitations of this review should be noted:

Study heterogeneity: Technologies, implementation methods, and outcomes varied greatly, making direct comparisons challenging. While meta-analyses were performed where appropriate, much of the synthesis remains narrative.

Publication bias: Failed implementations are rarely published. True effect sizes may be 10–20% lower than reported.

Short follow-up periods: Observed benefits over 12–18 months may not persist long-term. Some improvements, such as organizational culture change or enhanced data infrastructure, may only fully materialize over several years.

Geographic concentration: Most studies come from high-income countries, limiting generalizability to resource-constrained settings. The near absence of studies from sub-Saharan Africa represents a major gap.

Methodological limitations: Most primary studies are observational and cannot definitively establish causality. Unmeasured confounders, such as simultaneous quality improvement initiatives, may explain some benefits attributed to AI.

Contextual factors not fully captured: Organizational culture, leadership quality, staff capabilities, and patient populations vary widely and likely influence implementation success, but these factors are difficult to quantify.

4.6 Strengths

Despite these limitations, this review has several notable strengths:

Rigorous adherence to PRISMA guidelines, with exhaustive database searches, dual independent review, and validated quality assessment tools.

Inclusion of 52 studies, representing the largest systematic synthesis of real-world AI implementation in hospital management to date.

Broad coverage of administrative, clinical, and operational applications, providing a more complete picture than narrower reviews.

Quantitative meta-analyses where possible, complemented by subgroup and sensitivity analyses to explore heterogeneity and test robustness.

Implementation science perspective, focusing not only on whether AI works but also on what organizational factors make it successful across different contexts.

5. Conclusion

Artificial intelligence is no longer just an experimental curiosity—it has become a practical tool in hospital management. This systematic review of 52 studies demonstrates tangible improvements: 30–45% gains in administrative efficiency, 12–18% increases in diagnostic accuracy, an average 1.6-day reduction in hospital stay, and a 267% three-year return on investment. Adoption is accelerating, with 71% of surveyed hospitals now implementing some form of AI.

However, three important caveats temper this optimistic picture:

Implementation requires effort and investment: Data integration issues (77%) and training challenges (71%) highlight that AI success depends as much on organizational commitment as on technology alone.

Equity gaps are significant: The 46-percentage-point adoption gap between university hospitals (87%) and rural facilities (41%) risks widening healthcare disparities. Targeted policy interventions are essential to ensure AI benefits all.

Evidence is incomplete: Short follow-ups, geographic concentration in high-income countries, methodological limitations, and potential publication bias remain challenges.

Looking forward, priorities include long-term outcome studies, implementation science research, equity-focused evaluations, and standardized assessment frameworks. Emerging technologies such as large language models and federated learning are promising, but they require careful evaluation.

For hospital administrators, the message is clear: AI can deliver substantial value, but success requires early stakeholder engagement, investment in training and organizational change, targeted pilot projects, careful vendor selection, and iterative refinement rather than aiming for perfect initial deployment.

For policymakers, ensuring equitable access is crucial. Infrastructure support for under-resourced hospitals, shared services models, technical assistance, and regulatory clarity can help level the playing field. Reimbursement models should recognize and reward AI-driven quality improvements.

Ultimately, AI is a powerful tool—but not a magical solution. Its impact depends on thoughtful implementation, evidence-based decision-making, strong organizational commitment, and attention to equity. This review provides a solid evidence base to guide hospitals and policymakers in navigating the AI journey.

6. References

1. W. H. Organization, Advancing the responsible use of digital technologies in global health: A report of the WHO Science Council. World Health Organization, 2025. Accessed: Nov. 10, 2025. [Online]. Available:

https://books.google.com/books?hl=fr&lr=&id=q8-KEQAAQBAJ&oi=fnd&pg=PR4&dq=World+Health+Organization.+Global+Strategy+on+Digital+Health+2020-2025.+Geneva:+WHO%3B+2021.&ots=g8UorjXWnv&sig=NbVnJ542KZozt7nTlJbPQYBiMgQ

2. J. M. McGinnis, L. Stuckhardt, R. Saunders, and M. Smith, ‘Best care at lower cost: the path to continuously learning health care in America’, 2013, Accessed: Nov. 10, 2025. [Online]. Available: https://books.google.com/books?hl=fr&lr=&id=_wUw6XCFqGwC&oi=fnd&pg=PR1&dq=1.%09Institute+of+Medicine.+Best+Care+at+Lower+Cost:+The+Path+to+Continuously+Learning+Health+Care+in+America.+Washington,+DC:+National+Academies+Press%3B+2012.&ots=0Mozxbgizp&sig=gx1WuLBL0WBBaFG9Vt-cHLbJsGM

3. S. Scarpetta and C. di Noia, ‘Pensions at a Glance 2023: OECD AND G20 INDICATORS.’, Pensions at a Glance, 2023, Accessed: Nov. 10, 2025. [Online]. Available: https://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=19954026&asa=N&AN=177979553&h=dWHlZgac6mWk6AMKQ7uf0WGUQbU9w8uaC45C7vdF00kmpd8BZgGmgn9sfYMEO60nzD26flXjtAcz3f40YGv6cw%3D%3D&crl=f

4. E. J. Topol, ‘High-performance medicine: the convergence of human and artificial intelligence’, Nature medicine, vol. 25, no. 1, pp. 44–56, 2019.

5. K.-H. Yu, A. L. Beam, and I. S. Kohane, ‘Artificial intelligence in healthcare’, Nature biomedical engineering, vol. 2, no. 10, pp. 719–731, 2018.

6. Esteva et al., ‘A guide to deep learning in healthcare’, Nature medicine, vol. 25, no. 1, pp. 24–29, 2019.

7. T. Davenport and R. Kalakota, ‘The potential for artificial intelligence in healthcare’, Future healthcare journal, vol. 6, no. 2, pp. 94–98, 2019.

8. Rajkomar, J. Dean, and I. Kohane, ‘Machine Learning in Medicine’, N Engl J Med, vol. 380, no. 14, pp. 1347–1358, Apr. 2019, doi: 10.1056/NEJMra1814259.

9. F. Jiang et al., ‘Artificial intelligence in healthcare: past, present and future’, Stroke and vascular neurology, vol. 2, no. 4, 2017, Accessed: Nov. 10, 2025. [Online]. Available: https://svn.bmj.com/Content/2/4/230.abstract

10. R. Vaishya, M. Javaid, I. H. Khan, and A. Haleem, ‘Artificial Intelligence (AI) applications for COVID-19 pandemic’, Diabetes & Metabolic Syndrome: Clinical Research & Reviews, vol. 14, no. 4, pp. 337–339, 2020.

11. J. Bullock, A. Luccioni, K. H. Pham, C. S. N. Lam, and M. Luengo-Oroz, ‘Mapping the landscape of artificial intelligence applications against COVID-19’, Journal of Artificial Intelligence Research, vol. 69, pp. 807–845, 2020.

12. S. Lalmuanawma, J. Hussain, and L. Chhakchhuak, ‘Applications of machine learning and artificial intelligence for Covid-19 (SARS-CoV-2) pandemic: A review’, Chaos, Solitons & Fractals, vol. 139, p. 110059, 2020.

13. B. McCall, ‘COVID-19 and artificial intelligence: protecting health-care workers and curbing the spread’, The Lancet Digital Health, vol. 2, no. 4, pp. e166–e167, 2020.

14. R. M. Wehbe et al., ‘DeepCOVID-XR: An Artificial Intelligence Algorithm to Detect COVID-19 on Chest Radiographs Trained and Tested on a Large U.S. Clinical Data Set’, Radiology, vol. 299, no. 1, pp. E167–E176, Apr. 2021, doi: 10.1148/radiol.2020203511.

15. W. Naudé, ‘Artificial intelligence vs COVID-19: limitations, constraints and pitfalls’, AI & Soc, vol. 35, no. 3, pp. 761–765, Sep. 2020, doi: 10.1007/s00146-020-00978-0.

16. S. Reddy, S. Allan, S. Coghlan, and P. Cooper, ‘A governance model for the application of AI in health care’, Journal of the American medical informatics association, vol. 27, no. 3, pp. 491–497, 2020.

17. C. J. Kelly, A. Karthikesalingam, M. Suleyman, G. Corrado, and D. King, ‘Key challenges for delivering clinical impact with artificial intelligence’, BMC Med, vol. 17, no. 1, p. 195, Dec. 2019, doi: 10.1186/s12916-019-1426-2.

18. J. S. Roppelt, D. K. Kanbach, and S. Kraus, ‘Artificial intelligence in healthcare institutions: A systematic literature review on influencing factors’, Technology in society, vol. 76, p. 102443, 2024.

19. Kamel Rahimi et al., ‘Implementing AI in hospitals to achieve a learning health system: systematic review of current enablers and barriers’, Journal of medical Internet research, vol. 26, p. e49655, 2024.

20. S. V. Bhagat and D. Kanyal, ‘Navigating the future: the transformative impact of artificial intelligence on hospital management-a comprehensive review’,

Cureus, vol. 16, no. 2, 2024, Accessed: Nov. 10, 2025. [Online]. Available: https://www.cureus.com/articles/219582-navigating-the-future-the-transformative-impact-of-artificial-intelligence-on-hospital-management--a-comprehensive-review.pdf

21. D. A. Hashimoto, G. Rosman, D. Rus, and O. R. Meireles, 'Artificial intelligence in surgery: promises and perils', Annals of surgery, vol. 268, no. 1, pp. 70–76, 2018.

22. X. Liu et al., 'Correction to Lancet Digital Health 2019; 1: e271–97 (The Lancet Digital Health (2019) 1 (6)(e271–e297),(S2589750019301232),(10.1016/S2589-7500 (19) 30123-2))', The Lancet Digital Health, vol. 1, no. 7, pp. e334–e334, 2019.

23. M. Nagendran et al., 'Artificial intelligence versus clinicians: systematic review of design, reporting standards, and claims of deep learning studies', bmj, vol. 368, 2020, Accessed: Nov. 10, 2025. [Online]. Available: https://www.bmj.com/content/368/bmj.m689.abstract

24. H. Ibrahim, X. Liu, N. Zariffa, A. D. Morris, and A. K. Denniston, 'Health data poverty: an assailable barrier to equitable digital health care', The Lancet Digital Health, vol. 3, no. 4, pp. e260–e265, 2021.

25. D. S. Char, N. H. Shah, and D. Magnus, 'Implementing machine learning in health care—addressing ethical challenges', The New England journal of medicine, vol. 378, no. 11, p. 981, 2018.

26. R. B. Parikh, S. Teeple, and A. S. Navathe, 'Addressing bias in artificial intelligence in health care', Jama, vol. 322, no. 24, pp. 2377–2378, 2019.

27. M. J. Page et al., 'The PRISMA 2020 statement: an updated guideline for reporting systematic reviews', bmj, vol. 372, 2021, Accessed: Nov. 10, 2025. [Online]. Available: https://www.bmj.com/content/372/bmj.n71.short

28. J. A. Sterne et al., 'RoB 2: a revised tool for assessing risk of bias in randomised trials', bmj, vol. 366, 2019, Accessed: Nov. 10, 2025. [Online]. Available: https://www.bmj.com/content/366/bmj.l4898.short

29. J. A. Sterne et al., 'ROBINS-I: a tool for assessing risk of bias in non-randomised studies of interventions', bmj, vol. 355, 2016, Accessed: Nov. 10, 2025. [Online]. Available: https://www.bmj.com/CONTENT/355/BMJ.I4919.abstract

30. G. A. Wells et al., 'The Newcastle-Ottawa Scale (NOS) for assessing the quality of nonrandomised studies in meta-analyses', 2000, Accessed: Nov. 10, 2025. [Online]. Available: https://scholar.archive.org/work/zuw33wskgzf4bceqgi7opslsre/access/wayback/www3.med.unipmn.it/dispense_ebm/2009-2010/Corso%20Perfezionamento%20EBM_Faggiano/NOS_oxford.pdf

31. M. Campbell et al., 'Synthesis without meta-analysis (SWiM) in systematic reviews: reporting guideline', bmj, vol. 368, 2020, Accessed: Nov. 10, 2025. [Online]. Available: https://www.bmj.com/content/368/bmj.l6890.abstract

32. R. M. (RevMan)[Computer program, 'Version 5.4, The Cochrane Collaboration'. The Cochrane Collaboration Copenhagen: The Nordic Cochrane Centre, 2020.

33. R. M. Wachter and E. Brynjolfsson, 'Will generative artificial intelligence deliver on its promise in health care?', Jama, vol. 331, no. 1, pp. 65–69, 2024.

34. M. P. Sendak, M. Gao, N. Brajer, and S. Balu, 'Presenting machine learning model information to clinical end users with model facts labels', NPJ digital medicine, vol. 3, no. 1, p. 41, 2020.

35. E. Wu, K. Wu, R. Daneshjou, D. Ouyang, D. E. Ho, and J. Zou, 'How medical AI devices are evaluated: limitations and recommendations from an analysis of FDA approvals', Nature Medicine, vol. 27, no. 4, pp. 582–584, 2021.

36. S. Benjamens, P. Dhunnoo, and B. Meskó, 'The state of artificial intelligence-based FDA-approved medical devices and algorithms: an online database', NPJ digital medicine, vol. 3, no. 1, p. 118, 2020.

37. E. J. Topol, 'Welcoming new guidelines for AI clinical research', Nature medicine, vol. 26, no. 9, pp. 1318–1320, 2020.

38. J. Guo and B. Li, 'The Application of Medical Artificial Intelligence Technology in Rural Areas of Developing Countries', Health Equity, vol. 2, no. 1, pp. 174–181, Aug. 2018, doi: 10.1089/heq.2018.0037.

39. M. E. Matheny, D. Whicher, and S. T. Israni, 'Artificial intelligence in health care: a report from the National Academy of Medicine', Jama, vol. 323, no. 6, pp. 509–510, 2020.

40. R. Hillestad et al., ‘Can Electronic Medical Record Systems Transform Health Care? Potential Health Benefits, Savings, And Costs’, Health Affairs, vol. 24, no. 5, pp. 1103–1117, Sep. 2005, doi: 10.1377/hlthaff.24.5.1103.

41. J. Walker, E. Pan, D. Johnston, J. Adler-Milstein, D. W. Bates, and B. Middleton, ‘The Value Of Health Care Information Exchange And Interoperability: There is a business case to be made for spending money on a fully standardized nationwide system.’, Health Affairs, vol. 24, no. Suppl1, pp. W5-10-W5-18, Jan. 2005, doi: 10.1377/hlthaff.W5.10.

42. M. Hassan, A. Kushniruk, and E. Borycki, ‘Barriers to and facilitators of artificial intelligence adoption in health care: scoping review’, JMIR Human Factors, vol. 11, p. e48633, 2024.

43. M. I. Ahmed, B. Spooner, J. Isherwood, M. Lane, E. Orrock, and A. Dennison, ‘A systematic review of the barriers to the implementation of artificial intelligence in healthcare’, Cureus, vol. 15, no. 10, 2023, Accessed: Nov. 11, 2025. [Online]. Available: https://www.cureus.com/articles/170025-a-systematic-review-of-the-barriers-to-the-implementation-of-artificial-intelligence-in-healthcare.pdf