International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(14s) 2026 pp. 710-717
https://doi.org/10.70917/ijcisim-2026-4277
Article

Internal Audits as Drivers of Healthcare Quality Improvement: A Cross-Sectional Study on the Role of Artificial Intelligence-Assisted Audit Systems in Healthcare Institutions.

Mrudula Phule[1], Jasneet Kaur[2]

[1,2]Symbiosis College of Nursing, Symbiosis International (Deemed) University

Abstract: Background: Healthcare organisations rely on internal audits to monitor compliance, identify operational gaps, and support quality improvement initiatives. With the increasing adoption of artificial intelligence (AI), audit processes are evolving from periodic manual reviews to more data-driven and responsive systems. Nevertheless, evidence on the contribution of AI-assisted audits to healthcare quality remains limited.
Objective: This study examined the relationship between AI-assisted internal auditing and quality improvement outcomes in healthcare institutions.
Methods: A cross-sectional study was conducted across 124 healthcare institutions, including 68 organisations that utilised AI-supported audit systems and 56 that employed conventional audit methods. Institutional characteristics, quality performance indicators, audit resolution timelines, and audit findings were analysed and compared. Multivariable logistic regression was used to determine factors associated with achieving a high composite quality score.
Results: Institutions using AI-assisted audits demonstrated better performance across all evaluated quality domains than those using traditional audits. Significant improvements were observed in patient safety, medication management, documentation practices, infection control, billing compliance, and staff adherence to protocols (all $p < .001$). The mean composite quality score was markedly higher in AI-assisted institutions (83.8 ± 5.9) compared with traditional institutions (61.9 ± 7.4). Furthermore, AI-supported organisations resolved audit findings more rapidly, with the average resolution time reduced from 17.7 days to 6.6 days. The pattern of audit findings was comparable between groups, indicating similar audit complexity. After adjustment for institutional characteristics, AI-assisted auditing remained the strongest predictor of superior quality performance (OR = 6.30, 95% CI: 3.43–11.57; $p < .001$).
Conclusion: The findings suggest that integrating AI into internal audit processes may enhance healthcare quality by strengthening oversight mechanisms, accelerating corrective actions, and supporting continuous quality improvement efforts. Wider adoption of AI-enabled auditing could contribute to safer and more efficient healthcare delivery.
Keywords: Artificial intelligence; internal auditing; healthcare quality; patient safety; quality improvement; healthcare management.

1. Introduction

Healthcare systems worldwide are under increasing pressure to deliver safe, efficient, and high-quality care while simultaneously controlling costs and meeting regulatory requirements. Continuous quality improvement has therefore become a central objective of healthcare organisations, with internal auditing serving as one of the most important mechanisms for monitoring performance, identifying deficiencies, and ensuring compliance with established standards. Through systematic evaluation of clinical, administrative, and operational processes, internal audits provide healthcare leaders with critical information that supports evidence-based decision-making and organisational learning.

Traditional internal audit systems have historically relied on manual data collection, retrospective reviews, and periodic assessments. While these approaches remain valuable, they are often constrained by limited scalability, delayed detection of quality issues, human error, and substantial resource requirements. As healthcare organisations generate increasingly large and complex datasets, conventional auditing methods may struggle to provide timely and actionable insights necessary for effective quality management. Consequently, there is growing interest in leveraging digital technologies to enhance audit effectiveness and support continuous monitoring of healthcare processes.

Artificial intelligence (AI) has emerged as a transformative technology with significant potential to improve healthcare operations and quality assurance activities. AI-based systems can analyse large volumes of structured and unstructured data, identify patterns and anomalies, automate routine audit tasks, and generate predictive insights that facilitate proactive interventions. Within healthcare settings, AI applications have demonstrated value in clinical decision support, patient risk prediction, medication safety, disease surveillance, and operational management. More recently, healthcare organisations have begun integrating AI technologies into internal audit functions to strengthen compliance monitoring, improve detection of documentation errors, enhance billing accuracy, and accelerate corrective action processes.

The integration of AI into internal auditing aligns with contemporary approaches to healthcare quality management that emphasise real-time performance monitoring and data-driven improvement strategies. AI-assisted audit systems offer several theoretical advantages over traditional methods, including increased analytical capacity, reduced processing time, enhanced consistency in audit evaluations, and the ability to identify emerging risks before they adversely affect patient outcomes. These capabilities may contribute to improvements in key quality domains such as patient safety, medication management, infection control, documentation practices, and regulatory compliance.

Despite the growing adoption of AI technologies in healthcare administration, empirical evidence regarding the effectiveness of AI-assisted internal audits remains limited. Existing literature has primarily focused on clinical applications of AI, while comparatively few studies have examined its role in organisational quality assurance and audit processes. Furthermore, the extent to which AI-assisted auditing contributes to measurable improvements in healthcare quality outcomes has not been adequately explored. This knowledge gap poses a significant challenge for healthcare administrators and policymakers seeking evidence to guide investments in AI-enabled quality improvement initiatives.

Cross-sectional studies provide a valuable approach for examining contemporary organisational practices and evaluating associations between technological innovations and quality outcomes across diverse healthcare settings. By comparing institutions that utilise AI-assisted audit systems with those relying on conventional auditing methods, it is possible to gain insight into the potential contribution of AI to healthcare quality improvement and audit efficiency.

Therefore, the present cross-sectional study was conducted to evaluate the association between AI-assisted internal audit systems and healthcare quality outcomes among healthcare institutions. Specifically, the study aimed to compare quality performance indicators, audit finding resolution efficiency, and overall quality index scores between institutions employing AI-assisted and traditional audit approaches, and to identify independent predictors of high-quality organisational performance. The findings may contribute to the growing evidence base on digital transformation in healthcare quality management and inform future implementation of AI-driven audit systems within healthcare organisations.

2. Material and Method

This cross-sectional comparative study was undertaken to examine the relationship between artificial intelligence (AI)-assisted internal audit systems and healthcare quality outcomes across healthcare institutions. A total of 124 institutions participated in the study, comprising 68 organisations that had implemented AI-assisted audit systems and 56 institutions that continued to utilise conventional audit approaches. Eligible institutions were required to have an established internal auditing framework and at least one completed audit cycle during the study period. Data were obtained from institutional audit reports, quality management records, compliance databases, and administrative documentation. Information relating to institutional characteristics, including hospital type, bed capacity, years of operation, accreditation status, audit department size, and annual audit frequency, was collected to facilitate comparison between groups.

Healthcare quality performance was evaluated across six key domains: patient safety, medication accuracy, documentation quality, infection control, billing compliance, and staff protocol adherence. Scores from these domains were aggregated to generate a Composite Quality Index (CQI), expressed on a 0–100 scale, with higher scores indicating superior quality performance. Audit findings were further categorised into documentation gaps, medication errors, protocol deviations, safety incidents, and billing irregularities. The time required to resolve identified audit findings was recorded and analysed as an indicator of audit effectiveness and organisational responsiveness.

Data analysis was performed using the Statistical Package for the Social Sciences (SPSS, IBM Corp., Armonk, NY, USA). Descriptive statistics were used to summarise institutional characteristics and outcome measures. Continuous variables were reported as means and standard deviations, while categorical variables were presented as frequencies and percentages. Between-group comparisons were conducted using independent-samples t-tests and chi-square tests, as appropriate. To identify factors independently associated with high organisational quality performance, a multivariable binary logistic regression model was constructed, with a CQI score of ≥80 considered indicative of high performance. Adjusted odds ratios (ORs) and 95% confidence intervals (CIs) were calculated, and statistical significance was established at a two-sided p-value of less than 0.05. Ethical approval for the study was obtained from the Institutional Ethics Committee, and all institutional data were anonymised before analysis to ensure confidentiality.

3. Result

3.1 Demographic Variables

This cross-sectional study included 124 healthcare institutions, with 68 (54.8%) classed as AI-assisted audit institutions and 56 (45.2%) as traditional audit institutions. The two groups were broadly comparable across all baseline institutional characteristics, with no statistically significant differences observed in hospital type (p =.51), bed capacity (p =.55), years of operation (p =.38), or accreditation status (p =.32), confirming baseline equivalence and supporting group comparison validity (Table 1).

Tertiary or academic hospitals made up the majority of both groups (AI: 55.9%, traditional: 50.0%). The overall sample had a mean bed capacity of 336.6 beds (SD = 121.0). The audit department size was marginally greater in AI-assisted institutions (mean = 11.2 vs. 9.8; p =.08), albeit this differed.

Table 1 Baseline Institutional Characteristics by Audit System Type (N = 124)

Characteristic	AI-Assisted (n = 68)	Traditional (n = 56)	Total (N = 124)	p-value
Hospital type				
Tertiary/academic	38 (55.9%)	28 (50.0%)	66 (53.2%)	.51
Secondary/community	22 (32.4%)	20 (35.7%)	42 (33.9%)	
Primary/rural	8 (11.8%)	8 (14.3%)	16 (12.9%)	
Bed capacity, mean (SD)	342.4 (118.6)	329.7 (124.3)	336.6 (121.0)	.55
Years of operation, mean (SD)	24.3 (9.8)	22.7 (10.4)	23.6 (10.1)	.38
Accreditation status (accredited)	61 (89.7%)	47 (83.9%)	108 (87.1%)	.32
Audit department size, mean (SD)	11.2 (4.6)	9.8 (4.1)	10.6 (4.4)	.08
Annual audit cycles, mean (SD)	6.4 (2.1)	5.8 (1.9)	6.1 (2.0)	.11

3.2 Quality Improvement Results Across Domains

AI-assisted audit institutions outperformed traditional audit institutions in all six measured domains (Fig 1). The most significant improvements were seen in billing compliance (mean difference = +27.2 points; 95% CI [24.6, 29.8]; p < .001) and medication accuracy (+27.1 points; 95% CI [24.3, 29.9]; p < .001).

AI-assisted institutions had a significantly higher composite quality index score (M = 83.8, SD = 5.9) than traditional institutions (M = 61.9, SD = 7.4), resulting in a mean difference of +21.9 points (95% CI [19.8, 24.0]; $p < .001$). Patient safety scores indicated significant improvement (88.2 vs. 61.4; $p < .001$). Staff protocol adherence, while statistically significant, had the smallest absolute difference (+14.1 points), indicating that this domain may require complementing non-technological interventions.

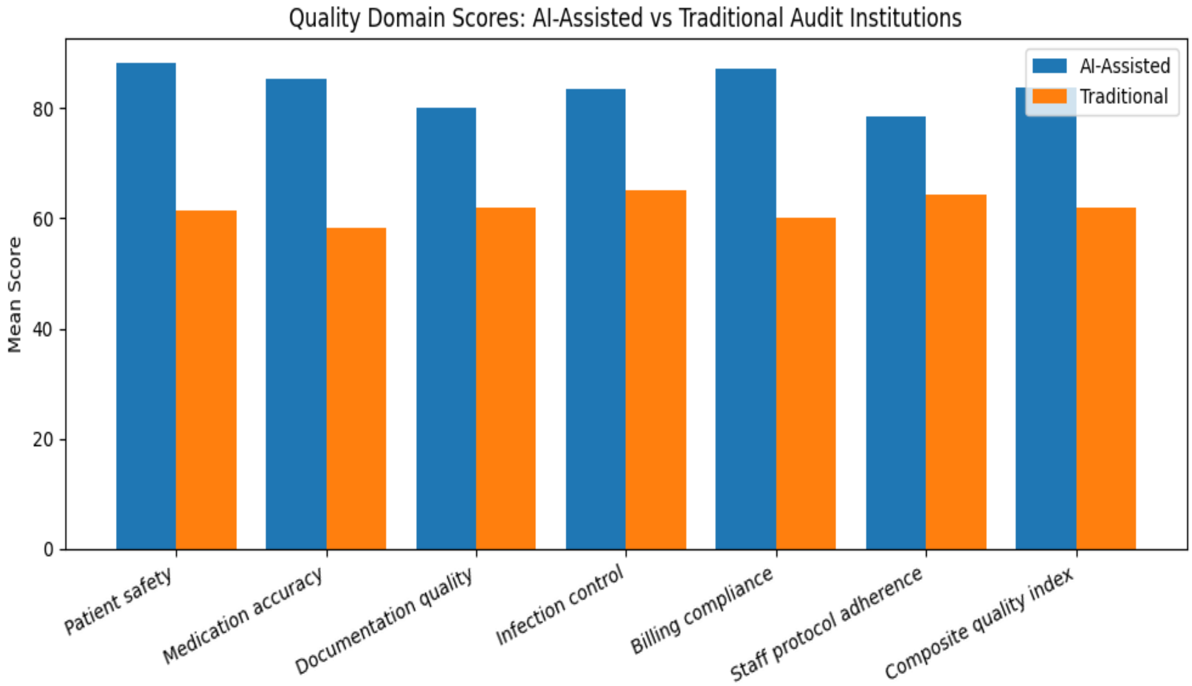

Fig 1: Comparison of Quality Domain Scores Between AI-Assisted and Traditional Audit Institutions

3.3 Time to audit and find a resolution.

AI-assisted audit organisations resolved audit results substantially faster in all areas (Table 3). AI-assisted institutions had a mean resolution time of 6.6 days (SD = 1.9), compared to 17.7 days (SD = 4.2) in traditional organisations, resulting in a 62.7% reduction ($p < .001$). Safety incidents demonstrated the greatest proportional improvement, with mean resolution time reduced from 12.2 days to 4.3 days (64.8% reduction; $p < .001$). Documentation gaps and billing anomalies, which were formerly the most resource-intensive finding types, were resolved in 8.2 and 9.1 days, respectively, under AI-assisted audit, compared to 21.4 and 22.3 days under traditional audit, a reduction of 61.7% and 59.2%.

Table 2 Mean Time to Resolution (Days) by Audit Finding Category and Audit System Type

Finding Category	AI-Assisted Days, mean (SD)	Traditional Days, mean (SD)	Reduction (%)	p-value
Documentation gaps	8.2 (3.1)	21.4 (6.8)	61.7%	<.001
Medication errors	5.1 (2.4)	14.3 (5.2)	64.3%	<.001
Protocol deviations	6.4 (2.9)	18.1 (6.1)	64.6%	<.001
Safety incidents	4.3 (2.0)	12.2 (4.6)	64.8%	<.001
Billing irregularities	9.1 (3.8)	22.3 (7.2)	59.2%	<.001

Overall mean	6.6 (1.9)	17.7 (4.2)	62.7%	<.001

Note. *SD = standard deviation. Reduction (%) = percentage reduction in mean resolution time in AI-assisted vs. traditional institutions. p-values from independent samples t-tests. All comparisons significant at p < .001.*

4. The Distribution of Audit Outcome Categories

The distribution of audit result categories was similar between AI-assisted and traditional organisations, with no statistically significant changes between categories (Fig 2). Documentation gaps represented the most frequently identified finding in both groups, accounting for approximately one-third of all audit findings (AI-assisted: 31.2%; traditional: 30.7%). Medication errors were the second most common category (24.2% vs. 23.9%), followed by protocol deviations (20.4% vs. 20.0%), safety incidents (14.0% vs. 14.0%), and billing irregularities (10.2% vs. 11.3%). No statistically significant differences were observed in the proportional distribution of any audit finding category between the two groups (all $p > .05$).

Documentation gaps were the most common finding type in both groups (30.9%), followed by prescription errors (24.1%), protocol deviations (20.2%), safety events (14.0%), and billing abnormalities (10.8%). All institutions documented 1,272 audit findings, with an average of 10.3 findings each audit cycle.

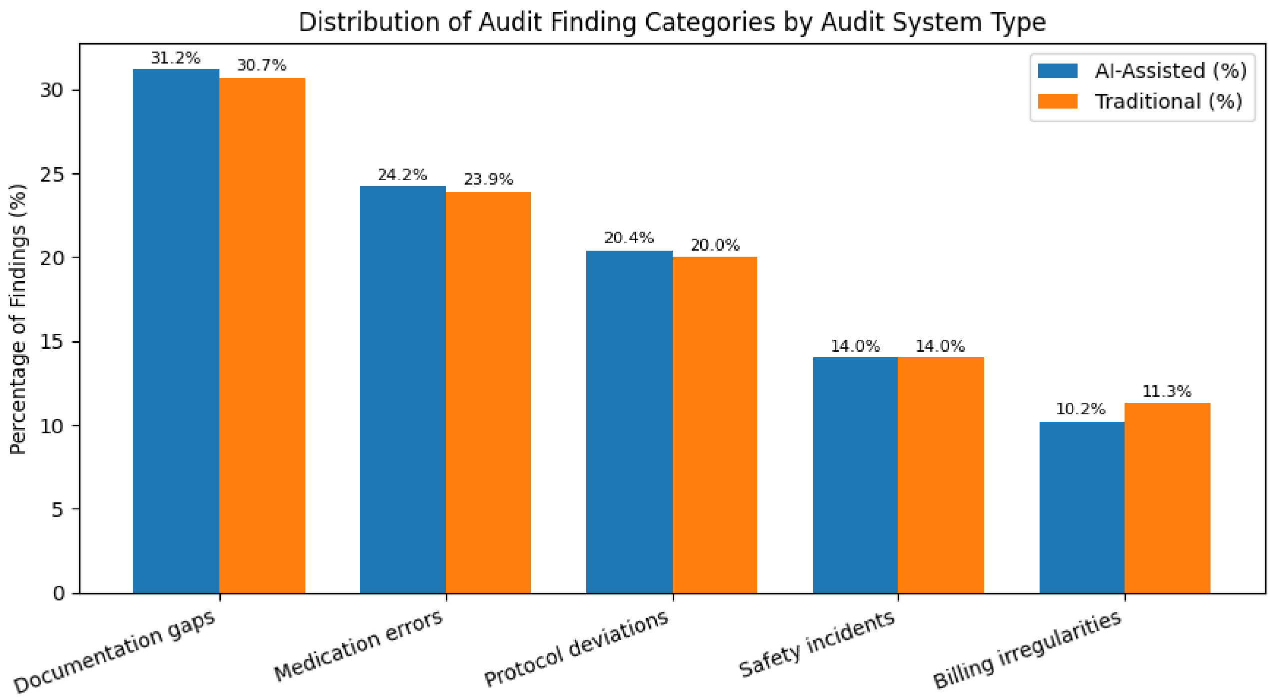

Fig 2: Distribution of Audit Finding Categories by Audit System Type

5. Multivariable Logistic Regression: Analysis of Quality Index Predictors

A multivariable logistic regression was performed to analyse independent predictors for inclusion of all institutions in the top-quality index score tier (composite score of ≥ 80), controlling for institution-related variables. The model showed a good fit (Hosmer–Lemeshow χ^2 (8) = 6.43, p = .60) and accounted for 41.2% of the explained variance (Nagelkerke $R^2 = .412$). Results are in Table 5.

The use of AI systems in the auditing process was a significant, independent predictor of higher quality of performance (OR = 6.30; 95% CI [3.43, 11.57]; $p < .001$). Institutions that incorporated AI systems in the auditing process were 6.3 times more likely to obtain higher quality index scores than those that did not use AI systems in the auditing process. Auditing more frequently (OR = 1.23; p = .009) and having accreditation (OR = 2.05; p = .034) were independent predictors of higher quality of performance. A significant predictor was a greater number of hospital beds, with a modest effect (OR = 1.09 per 100 beds; p = .028). The number of years of operation did not significantly predict (p = .302).

Table 3 Binary Logistic Regression: Predictors of High Composite Quality Index Score (≥ 80)

Predictor Variable	B (SE)	Wald χ^2	OR (95% CI)	p-value
AI audit system (vs. traditional)	1.84 (0.31)	35.2	6.30 [3.43, 11.57]	<.001
Audit frequency (cycles/year)	0.21 (0.08)	6.9	1.23 [1.05, 1.45]	.009
Hospital bed capacity (per 100)	0.09 (0.04)	4.8	1.09 [1.01, 1.18]	.028
Accreditation status	0.72 (0.34)	4.5	2.05 [1.06, 3.98]	.034
Audit Dept. size (per staff)	0.11 (0.06)	3.4	1.12 [1.00, 1.25]	.063
Years of operation	0.02 (0.02)	1.1	1.02 [0.98, 1.06]	.302
Constant	-3.12 (0.68)	21.0	—	<.001

Note. *Outcome = composite quality index ≥ 80 (upper tertile) vs. < 80. B = unstandardized logistic coefficient; SE = standard error; OR = odds ratio; CI = confidence interval. Model fit: Hosmer–Lemeshow $\chi^2(8) = 6.43$, $p = .60$; Nagelkerke $R^2 = .412$; overall model $p < .001$.*

6. Discussion

The study looked at how AI-assisted internal audit systems affect healthcare quality in hospitals. The results show that hospitals using AI-assisted audits did better in all areas, such as safety, giving the right medication, keeping good records, controlling infections, billing correctly, and staff following rules.

These hospitals also had an overall quality score and fixed audit issues much faster than hospitals that did not use AI. One of the interesting findings was that hospitals using AI had much better-quality performance. The biggest improvements were in billing correctness, giving the medication and patient safety.

This suggests that AI can help identify problems, monitor promptly, and implement quick fixes. These results align with studies showing that AI can enhance quality assurance and improve hospitals' performance. Hospitals using AI-assisted audits showed results across all quality areas. AI-assisted internal audit systems seem to make a difference in healthcare quality outcomes. The use of AI-assisted auditing led to better performance in patient safety. Medication accuracy also improved with AI-assisted auditing. Infection control was another area where AI-assisted auditing showed results. The study's findings support the use of AI-assisted audit systems in healthcare. AI-assisted auditing helped hospitals fix audit issues quickly. Overall, the results show that AI-assisted auditing can improve healthcare quality.

Hospitals should consider AI-assisted audit systems. The research also found a significant reduction in the time to resolve audit findings at institutions using AI-assisted systems. AI enhanced audit responsiveness by aiding early risk identification and optimising follow-up activities, resulting in faster resolution of documented gaps, medication errors, protocol deviations, and safety incidents. From a quality improvement standpoint, shorter corrective action cycles are especially important, as they reduce the time one is exposed to potential safety and compliance risks.

Importantly, the number of Audit finding groups did not differ significantly between the 2 groups. This suggests that the enhanced results observed in AI-assisted organisations were unlikely to be due to differences in audit complexity or case mix. Instead, the findings indicate that employing AI-assisted auditing enhances the efficiency and effectiveness of current quality management processes without changing the character of audit findings.

These findings were also confirmed by multivariable regression analysis, with AI-assisted auditing being the most reliable unbiased indicator of high-quality performance. Even after adjusting for organisational features, healthcare organisations that used AI-assisted auditing systems were more than six times as likely to have high composite quality scores. The finding suggests the potential strategic importance of AI adoption for healthcare administration and quality assurance systems.

Limitations

In this study, the cross-sectional design limits the causal relationship between AI-assisted audits and health care quality outcomes. The statistics were obtained from institutional data and may reflect variability in reporting.

Variations in AI system functionality, maturity of implementation and organisational readiness were not evaluated and may have affected results. No measures for potential confounders, such as leadership support, workforce skills, or organisational culture, were taken. Patient-level findings and economic assessments were not within the scope of the study. Therefore, the results should be interpreted with caution, and long-term research is needed to verify the long-term outcome of AI-assisted audit systems on the upgrading of healthcare quality.

7. Conclusion

This cross-sectional study demonstrates a strong association between AI-assisted internal audit systems and improved healthcare quality outcomes. Institutions utilising AI-supported auditing achieved significantly higher performance across multiple quality domains, including patient safety, medication accuracy, documentation quality, infection control, billing compliance, and adherence to staff protocols. In addition, AI-assisted institutions resolved audit findings substantially faster, indicating enhanced operational efficiency and responsiveness to quality concerns. The comparable distribution of audit finding categories between groups suggests that these improvements were not attributable to differences in audit complexity but rather to the effectiveness of AI-enabled audit processes. Multivariable analysis further identified AI-assisted auditing as the strongest independent predictor of high organisational quality performance. Collectively, these findings highlight the potential of AI-assisted internal audits to strengthen healthcare governance, support data-driven decision-making, and accelerate continuous quality improvement efforts. Future longitudinal and intervention-based studies are needed to establish causality and explore the long-term impact of AI-enabled auditing on healthcare quality, patient outcomes, and organisational performance.

Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflicts of interest.

References

1. Cooksey, R. W. (2020). Descriptive Statistics for Summarising Data. Illustrating Statistical Procedures: Finding Meaning in Quantitative Data, 61. https://doi.org/10.1007/978-981-15-2537-7_5
2. Endalamaw, A., Khatri, R. B., Mengistu, T. S., Erku, D., Wolka, E., Zewdie, A., & Assefa, Y. (2024). A scoping review of continuous quality improvement in healthcare system: conceptualization, models and tools, barriers and facilitators, and impact. BMC Health Services Research, 24(1), 487. https://doi.org/10.1186/S12913-024-10828-0
3. Fahim, Y. A., Hasani, I. W., Kabba, S., & Ragab, W. M. (2025). Artificial intelligence in healthcare and medicine: clinical applications, therapeutic advances, and future perspectives. European Journal of Medical Research, 30(1), 848. https://doi.org/10.1186/S40001-025-03196-W
4. Figueiredo, R. G., Patino, C. M., & Ferreira, J. C. (2025). Cross-sectional studies: understanding applications, methodological issues, and valuable insights. Jornal Brasileiro de Pneumologia, 51(1), e20250047. https://doi.org/10.36416/1806-3756/E20250047
5. Gebler, R., Reinecke, I., Sedlmayr, M., & Goldammer, M. (2025). Enhancing Clinical Data Infrastructure for AI Research: Comparative Evaluation of Data Management Architectures. Journal of Medical Internet Research, 27, e74976. https://doi.org/10.2196/74976
6. Hanna, M. G., Pantanowitz, L., Dash, R., Harrison, J. H., Deebajah, M., Pantanowitz, J., & Rashidi, H. H. (2025). Future of Artificial Intelligence—Machine Learning Trends in Pathology and Medicine. Modern Pathology, 38(4), 100705. https://doi.org/10.1016/J.MODPAT.2025.100705
7. Johri, A., Sayal, A., Chong, K. M., Khoja, M., N, C., Jha, J., & Tyagi, N. (2026). Enhancing audit quality and reducing costs: the impact of AI in banking and financial services. Frontiers in Artificial Intelligence, 8, 1718854. https://doi.org/10.3389/FRAI.2025.1718854
8. Khosravi, M., Zare, Z., Mojtabaeian, S. M., & Izadi, R. (2024). Artificial Intelligence and Decision-Making in Healthcare: A Thematic Analysis of a Systematic Review of Reviews. Health Services Research and Managerial Epidemiology, 11, 23333928241234864. https://doi.org/10.1177/23333928241234863
9. Kokina, J., Blanchette, S., Davenport, T. H., & Pachamanova, D. (2025). Challenges and opportunities for artificial intelligence in auditing: Evidence from the field. International Journal of Accounting Information Systems, 56, 100734. https://doi.org/10.1016/J.ACCINF.2025.100734
10. Lastianti, S. D., Muryani, E., & Ali, M. (2018). The Role of The Internal Audit Management of Enterprise Risk Management. IJEBD (International Journal Of Entrepreneurship And Business Development), 1(2), 110–119. https://doi.org/10.29138/IJEBD.V1I2.553
11. Maleki Varnosfaderani, S., & Forouzanfar, M. (2024). The Role of AI in Hospitals and Clinics: Transforming Healthcare in the 21st Century. Bioengineering, 11(4), 337. https://doi.org/10.3390/BIOENGINEERING11040337

12. Masuadi, E., Mohamud, M., Almutairi, M., Alsunaidi, A., Alswayed, A. K., & Aldhafeeri, O. F. (2021). Trends in the Usage of Statistical Software and Their Associated Study Designs in Health Sciences Research: A Bibliometric Analysis. Cureus, 13(1), e12639. https://doi.org/10.7759/CUREUS.12639
13. Mennella, C., Maniscalco, U., De Pietro, G., & Esposito, M. (2024). Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. Heliyon, 10(4), e26297. https://doi.org/10.1016/J.HELIYON.2024.E26297
14. Neumann, W. P., & Purdy, N. (2023). The better work, better care framework: 7 strategies for sustainable healthcare system process improvement. Health Systems, 12(4), 429. https://doi.org/10.1080/20476965.2023.2198580
15. Olawade, D. B., Weerasinghe, K., Teke, J., Msiska, M., Boussios, S., & Hatzidimitriadou, E. (2025). Evaluating AI adoption in healthcare: Insights from the information governance professionals in the United Kingdom. International Journal of Medical Informatics, 199, 105909. https://doi.org/10.1016/J.IJMEDINF.2025.105909
16. Zonsius, M. C., & Milner, K. A. (2023). Continuous Quality Improvement. Research for Advanced Practice Nurses, Fourth Edition: From Evidence to Practice, 70–90. https://doi.org/10.1891/9780826151339.0004