Journal of
Business and Strategic
Management
(JBSM)

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Journal of Business and Strategic Management
ISSN 2520-0402 (online)
Vol. 10, Issue No. 13, pp. 31 - 52, 2025
www.carijournals

Effect of Artificial Intelligence Adoption on Performance of Healthcare Sector in Kenya: A Case of Nairobi Public Hospitals

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Accepted: 4th August, 2025, Received in Revised Form: 28th August, 2025, Published: 4th September, 2025

ABSTRACT

Purpose: This study investigated the impact of Artificial Intelligence (AI) adoption on healthcare performance in public hospitals within Nairobi City County, Kenya. Despite AI's potential to transform healthcare through enhanced diagnostic accuracy, resource allocation, and operational efficiency, its adoption remained notably low in Nairobi's healthcare sector.

Methodology: The research adopted a descriptive correlational design to examine relationships between AI adoption and healthcare performance metrics, focusing on three key areas: AI adoption rates, system integration, and disease prediction capabilities. The study targeted healthcare professionals, administrators, and technical staff across public hospitals in Nairobi, with a population of 210 respondents and a sample size of 138, determined using Yamane's formula. Data collection utilized structured questionnaires administered to physicians, nurses, IT specialists, administrators, and policymakers between 2020 and 2024, examining adoption trends particularly in light of the COVID-19 pandemic's acceleration of digital healthcare transformation.

Findings: The findings revealed statistically significant positive relationships between all AI implementation dimensions and healthcare performance. Among them, AI utilization for disease prediction had the strongest impact explaining 44.6% of variance in performance followed closely by AI integration at 43.1%, and AI adoption rate contributed significantly at 41.7% of the variance. Healthcare performance metrics showed marked improvements, with service quality achieving the highest mean score (4.08), followed by treatment outcomes (3.98) and patient satisfaction (3.95). The study concludes that predictive AI applications provide the highest value for healthcare performance enhancement, while successful integration requires user-centered design and comprehensive technical support.

Unique Contribution to Theory, Practice and Policy: Key recommendations include establishing mandatory AI training programs, developing robust data governance frameworks, implementing phased adoption strategies, and creating AI transparency initiatives to address staff trust issues and maximize the demonstrated performance improvements across all implementation dimensions.

Key Words: *Adoption Rate of AI, Integration of AI, Utilization of AI in Predicting Emerging Diseases and Healthcare Performance*

Background of the Study

Access to healthcare is universally recognized as a fundamental human right. In 2015, the United Nations General Assembly adopted the Sustainable Development Goals (SDGs), with Goal 3 focused on ensuring healthy lives and promoting well-being for all at all ages (UN, 2015). Achieving this goal is increasingly tied to the strategic use of technology, particularly digital innovations like Artificial Intelligence (AI), which are being used to enhance healthcare systems around the world. In countries with well-developed infrastructure, AI has already improved diagnosis, treatment planning, and resource management, while in low- and middle-income countries, its potential is still being explored. In high-income nations such as China, the United States, and the United Kingdom, AI has been incorporated into mainstream healthcare systems to support clinical decisions and improve patient experiences. For instance, AI-powered platforms have helped health workers analyze patient feedback, track service quality, and respond faster to clinical needs (Secinaro et al., 2021). AI-supported nursing models have contributed to increased patient satisfaction, fewer treatment errors, and lower readmission rates (Wang, 2020). During the COVID-19 pandemic, machine learning applications were used to forecast transmission trends and allocate resources more efficiently (Jackline, 2022).

These successes have encouraged the global movement toward personalized and data-driven healthcare. The adoption of precision medicine—driven by AI tools that evaluate lifestyle and genetic factors—is now standard practice in many international hospitals (Aldoseri et al., 2023). While such developments are becoming routine in the global North, low-income regions are still adapting to basic digital healthcare systems. In Sub-Saharan Africa, AI has been introduced in some countries to help bridge service delivery gaps, though uptake remains slow. The region faces persistent challenges including poor infrastructure, limited funding, and low digital literacy among healthcare workers (Etori et al., 2023). Nonetheless, examples from countries like South Africa and Nigeria demonstrate progress. South Africa, in particular, has used AI tools for diagnostic support, targeting chronic illnesses and remote access problems (Behara et al., 2022). Kenya and Nigeria have trialed AI-based telemedicine systems to extend specialist care to underserved populations.

Despite these efforts, challenges such as unreliable data systems, limited policy frameworks, and concerns about data privacy have slowed progress. Researchers have called for stronger collaboration across sectors, improved regulatory support, and better training for healthcare staff to make AI more viable on the continent (Olawade et al., 2024; Owoyemi et al., 2020). Kenya's healthcare system is organized into six levels, with Level 6 hospitals serving as county referral centers. These facilities handle complex cases from lower-tier hospitals and provide a critical link between county services and national health programs. Nairobi County, being the capital, hosts some of the busiest and most resource-constrained Level 5 and 6 hospitals in the country. While Kenya has made efforts to improve its digital health systems—such as through the eHealth Policy (2016–2030)—implementation gaps remain.

Statement of the Problem

Adopting Artificial Intelligence (AI) technologies holds significant potential to transform healthcare by enhancing diagnostic accuracy, resource allocation, and operational efficiency. AI-driven innovations have improved healthcare systems worldwide, introducing predictive analytics for disease management, personalized treatment plans, and administrative automation (Aldoseri et al., 2023). However, AI remains notably underutilized in Nairobi County's healthcare sector, especially in public hospitals, where low adoption rates limit its potential impact on patient outcomes and system efficiency. In Nairobi, some healthcare providers have incorporated digital tools like eHealth and telemedicine, improving process efficiency, reducing costs, and reaching underserved patients, particularly those with chronic conditions (Christie, 2020). Despite these digital advances, traditional diagnostic methods predominate in Nairobi's healthcare facilities, leading to significant delays and suboptimal outcomes. According to the Kenya Health Service Delivery Indicator Survey (2018), patients in public hospitals face diagnostic delays of 36-48 hours, contributing to a 20% increase in mortality rates for treatable conditions. This diagnostic inefficiency indicates an urgent need for enhanced speed and resource management in the healthcare sector.

A study published in JAMA Network Open implemented an AI-based diagnostic system for cervical cancer screening in a Kenyan clinic, achieving high sensitivity rates of 96% to 100% and AUC values between 0.94 and 0.96 (Holmström et al., 2021). This system minimized diagnostic errors and improved early detection, demonstrating AI's potential to enhance diagnostic accuracy in resource-limited settings. By applying similar technologies, Nairobi's public hospitals could improve diagnostic efficiency and better meet patient needs. Despite this potential, several structural and operational challenges impede the integration of AI in these facilities.Research by Bukachi (2024) on the Challenges of AI Integration in Kenyan Healthcare highlights critical barriers, including limited awareness among healthcare professionals, low investment in AI infrastructure, data privacy concerns, and resistance to new technologies (Agyemang et al., 2022). These factors collectively hinder AI adoption despite its promise to improve healthcare quality and operational efficiency.

This study addresses these gaps by analyzing the factors influencing AI adoption in Nairobi's Public hospitals and evaluating AI's impact on healthcare performance. The research will offer practical recommendations for policymakers, healthcare administrators, and AI developers to enhance patient outcomes and operational efficiency in Nairobi's healthcare sector by exploring both barriers and opportunities for AI adoption. This study contributes to these efforts by investigating current AI use and the factors influencing its success in Nairobi's Public hospitals.

Objectives of the Study

i To assess the effect of the adoption rate of AI on the performance of the healthcare sector in Nairobi County ii To assess the effect of integration of AI on the performance of the healthcare sector in Nairobi County

iii To examine the utilization of AI in predicting emerging diseases on healthcare performance in Nairobi County

Literature Review

Artificial Intelligence on Adoption Rate

The adoption of AI within Kenya's healthcare sector has gained momentum in recent years, underpinned by both government support and private sector innovation. Globally, AI technologies, including diagnostic imaging tools, patient data monitoring algorithms, and clinical decision-support systems, have shown promise in enhancing the speed and accuracy of medical care (World Health Organization [WHO], 2021; Adepoju, 2023). Sub-Saharan Africa has embraced pilot AI programs in tuberculosis detection, maternal health, and malaria diagnostics, albeit unevenly, due to infrastructure disparities (Gavi, 2022; PATH, 2023). Kenya's positioning as a digital transformation leader in the region is evident in its National Artificial Intelligence Strategy (ICT Authority, 2023), which emphasizes ethical AI integration, with healthcare flagged as a priority sector. These efforts align with long-term policy goals such as Vision 2030 and the Kenya Digital Economy Blueprint, which underscore the role of innovation in delivering efficient public services (Chimole & Owade, 2021). Healthcare-specific digital infrastructure has seen gradual improvement. The Ministry of Health established a technological foundation for layering AI by implementing the Health Information System Interoperability Layer (IL), Afya Care program, and digitizing health records in select hospitals. These developments enhance AI readiness and data accessibility, creating enabling conditions for future AI applications in diagnostics, planning, and hospital operations.

Nairobi, as Kenya's capital and innovation hub, enjoys a higher concentration of resources and institutional capacities necessary for AI adoption. The city is home to major public hospitals, including Mama Lucy Hospital and Kenyatta National Hospital, as well as training institutions and innovation labs that support healthcare research and development (Okumu & Owade, 2020). Public–private collaborations have contributed to the early adoption of AI. Several hospitals in Nairobi have piloted AI-based triage systems and diagnostic tools through partnerships with technology companies and international donors. These engagements provide not only the technological input but also training, knowledge transfer, and financial support. However, such innovations tend to be localized, with only a few public hospitals benefiting from them, thus creating adoption gaps across the city. Moreover, the rollout of Universal Health Coverage (UHC) and the Health Sector Strategic and Investment Plan (2018–2023) has emphasized digital health as a key enabler of service delivery reform. Although not exclusively focused on AI, these strategic initiatives improve the organizational culture and system-wide readiness needed for AI adoption (Ministry of Health, 2022).

Despite Nairobi's relatively advanced infrastructure, several institutional challenges impede AI adoption in Level 5 and 6 public hospitals. A major hindrance is the fragmentation of digital systems. Many facilities lack harmonized electronic medical record systems, stable electricity, and high-speed internet, which are prerequisites for running AI applications (Okumu & Owade, 2020). Even when digital systems exist, interoperability remains limited. Human resources also pose a critical challenge. Most public hospitals operate under strained staffing levels and overwhelming patient loads. Many healthcare workers possess limited digital literacy, which affects their ability to adopt or trust AI-based solutions. Wanjiru and Kimathi (2021) highlight that tools imported from high-income countries often assume a digital maturity that Nairobi's healthcare system does not yet possess. These tools fail to account for documentation inconsistencies, language barriers, and workflow differences. Sociocultural skepticism further complicates the situation. Otieno and Achieng (2022) reported that clinicians remain wary of AI-generated diagnostics, fearing inaccuracy or misdiagnosis. Ethical concerns around data privacy, potential job loss, and decision accountability contribute to this resistance. These perceptions highlight the need for participatory design approaches that involve frontline users in the development and implementation of AI systems.

Closely tied to institutional limitations are workforce and funding constraints that directly affect AI adoption. The financial cost of AI implementation is substantial. Acquiring advanced software, hardware, and training requires investments that are often beyond the budgets of public health institutions (Federspiel et al., 2023). Hospitals must prioritize urgent patient needs and infrastructure maintenance over technological experimentation. Infrastructure inadequacy also remains a persistent barrier. Many Nairobi hospitals still lack robust data storage systems, secure networks, and server capacity needed to manage AI-powered platforms effectively. This technological lag hinders the integration of complex AI tools, particularly in facilities that have not been previously digitized (Okumu & Owade, 2020). Moreover, there is a severe shortage of AI expertise within the public health sector. Ofori et al. (2021) observe that while AI professionals are emerging in Kenya, most are absorbed by the private sector or migrate abroad in search of better incentives and career growth (Shiyyab et al., 2023). Local education institutions are only beginning to incorporate AI courses, and the current curriculum does not adequately prepare healthcare professionals to engage with AI systems (Owoyemi, 2020). This talent gap slows down the development and sustainability of AI projects within Nairobi's public healthcare system.

Kenya's healthcare sector lags behind industries such as finance and telecommunications in AI adoption. In the financial sector, AI is widely utilized for fraud detection, credit scoring, and customer profiling, thanks to a robust digital infrastructure and a regulatory framework that fosters innovation (De Almeida et al., 2021; Brand, 2022). Similarly, telecom companies utilize AI to optimize their networks, target customers effectively, and manage service delivery with high efficiency (Agyemang et al., 2022). These sectors have benefited from private capital investment, consistent policy environments, and data-rich ecosystems, making it easier to scale AI solutions.

In contrast, public healthcare struggles with underfunding, rigid procurement processes, and heightened scrutiny regarding ethics and patient safety (Karanja & Otieno, 2020). Nonetheless, cross-sectoral learning is possible. The introduction of regulatory sandboxes, pilot evaluations, and flexible procurement models from other sectors could help healthcare institutions fast-track the responsible adoption of AI if adapted appropriately.

Despite the challenges, several Kenyan innovations showcase the potential for localized AI adoption tailored to healthcare needs. Antimicro.ai, developed by clinicians at Narok Hospital, uses AI to predict patterns of antimicrobial resistance, guiding clinicians toward more effective antibiotic choices based on regional trends (Gavi, 2023). This helps reduce antibiotic misuse and enhances treatment accuracy. Ilara Health offers portable, AI-enabled diagnostic tools that analyze vital signs, such as lung sounds, to detect respiratory illnesses. Explicitly designed for low-resource settings, the devices integrate with mobile platforms and are currently in use across small clinics in Nairobi County (Ilara Health, 2023). These tools address gaps in basic diagnostics without requiring advanced infrastructure. Another innovation is AfyaRekod, a blockchain-AI hybrid platform that empowers patients to control and securely share their medical records across institutions. This addresses the challenge of fragmented medical histories and facilitates continuity of care (AfyaRekod, 2022). These examples demonstrate how context-specific innovation can circumvent systemic barriers to adoption. They highlight the role of local expertise, iterative development, and partnerships in scaling AI in public health.

Artificial Intelligence on Integration

The effect of AI integration on revenue growth in Nairobi County's public hospitals is multifaceted. Research by Auko et al. (2021) highlights that AI technologies play a pivotal role in augmenting revenue streams through several mechanisms. Improved diagnostics, driven by AI algorithms, enhance the accuracy and speed of identifying medical conditions, thereby increasing the volume of patients treated effectively. This leads to higher patient turnover and improved revenue for healthcare facilities. Personalized treatment plans, another significant contribution of AI, improve patient outcomes and satisfaction. AI enables the analysis of large datasets to tailor treatments to individual patient profiles, thereby enhancing the efficacy of interventions and patient compliance. This personalized approach not only improves health outcomes but also fosters patient loyalty, leading to repeat visits and increased revenue for healthcare providers in Nairobi County (Auko et al., 2021). Operational streamlining facilitated by AI also contributes to revenue growth. AI-driven systems optimize scheduling, resource allocation, and administrative tasks, reducing operational costs and increasing efficiency. For example, AI can predict patient no-shows and optimize appointment scheduling, ensuring that healthcare providers utilize their time effectively and maximize patient throughput (Okumu & Owade, 2020).

AI integration in Nairobi County's healthcare sector significantly impacts cost reduction and operational efficiency. Odekunle et al. (2020) emphasize that AI applications, such as predictive maintenance and resource optimization, streamline operations and reduce operational costs. By predicting equipment failures and scheduling timely maintenance, AI minimizes downtime and extends the lifespan of medical equipment, leading to substantial cost savings for healthcare facilities (Okumu & Owade, 2020). AI-driven automated processes and machine learning algorithms also optimize staffing and inventory management. These technologies analyze historical data and current trends to forecast demand accurately, ensuring that healthcare providers maintain optimal inventory levels and adequately staffed shifts. This precision reduces the costs associated with overstocking or underutilizing resources (Owoyemi et al., 2020). For instance, AI can predict peak times for patient visits and adjust staffing levels accordingly, thereby avoiding the expenses associated with both understaffing and overstaffing. AI-enabled decision-making tools enhance operational agility, enabling quicker responses to market changes and patient demands. Naidoo et al. (2022) discuss how AI systems can process vast amounts of data in real-time, providing healthcare managers with actionable insights. These insights enable rapid decision-making, such as reallocating resources during sudden surges in patient numbers or identifying inefficiencies in workflow processes that can be rectified promptly. This agility improves service delivery and reduces unnecessary operational expenses (Naidoo et al., 2022).

The correlation between AI adoption and heightened customer satisfaction in Nairobi County's healthcare sector is increasingly evident. Brand (2022) emphasizes that AI-driven personalized care significantly enhances the patient experience, leading to higher satisfaction levels. AI technologies enable the development of tailored treatment plans and health management strategies by analyzing patient data to provide personalized recommendations and interventions. AI-powered telemedicine solutions have revolutionized patient access to healthcare, particularly in Nairobi County. These solutions enable patients to consult with healthcare providers remotely, thereby reducing the need for in-person visits and minimizing waiting times. This convenience and accessibility significantly enhance patient satisfaction, particularly for those residing in remote areas or experiencing mobility issues (Brand, 2022). AI-driven telemedicine platforms offer real-time monitoring and follow-up, ensuring continuous and proactive patient care.

Despite the potential of AI integration to transform healthcare service delivery, numerous operational challenges persist. One major barrier is the lack of alignment between AI systems and existing clinical workflows. In many Public hospitals, clinicians must rely on manual patient records, which are often incomplete or inconsistently updated. Integrating AI into such fragmented systems poses significant difficulties and may introduce delays rather than efficiencies (Choudhury & Asan, 2020). Moreover, many AI tools are developed in isolation from the end users—clinicians, nurses, and administrators—resulting in poor system usability. Tools that do not fit naturally into the daily routines of health workers are often abandoned, regardless of their potential accuracy or usefulness (Nguyen et al., 2020). Resistance to change is another contributing factor; clinicians may distrust AI-generated recommendations, especially when these contradict their clinical intuition or experience (Celi et al., 2021). A further concern involves the format of AI outputs. If the predictions or alerts generated by AI tools are not presented in a clear, interpretable manner, they are unlikely to be acted upon. Explainability and user trust become paramount in this regard. AI models must provide not just answers, but also the reasoning behind them in formats understandable to non-technical medical staff (Ogunleye & Wang, 2020).

Artificial Intelligence on Utilization

The application of artificial intelligence (AI) in disease prediction has attracted growing interest in recent years, particularly in the areas of early detection, outbreak forecasting, and personalized risk profiling. AI-powered models have shown considerable promise in anticipating disease progression, identifying individuals at high risk, and enhancing preparedness for epidemics (Ali et al., 2021; Ogunleye & Wang, 2020). In sub-Saharan Africa, AI technologies are being considered as innovative responses to challenges associated with data gaps, constrained public health infrastructure, and uneven resource allocation, especially in surveillance and monitoring systems (Aruleba et al., 2021). However, several practical limitations hinder the widespread application of AI for disease forecasting, especially in low-resource contexts. A significant concern lies in the quality and reliability of health data used to train machine learning models. In many settings, health records remain fragmented, manually recorded, or inconsistently updated, leading to compromised model accuracy and reduced predictive value (Choudhury & Asan, 2020). Additionally, even when predictions are generated, the way outputs are presented often lacks clarity or clinical interpretability, making it difficult for healthcare providers to act on them in time-sensitive situations (Nguyen et al., 2020).

AI applications vary significantly across industries, influencing how organizations realize performance gains. In healthcare, AI emphasizes clinical accuracy and operational efficiency, particularly in diagnostic imaging, patient monitoring, and workflow automation (De Almeida et al., 2020). These implementations have a direct impact on the quality of service delivery and patient satisfaction. Conversely, sectors such as finance adopt AI for risk management and fraud detection. Algorithms assess transactional patterns and market data to inform investment strategies and ensure financial stability (De Almeida et al., 2020). The distinct goals—efficiency and trust in healthcare versus security and profit in finance—underscore the contextual customization required for successful AI adoption. Understanding these sectoral differences is crucial in developing policies and frameworks that maximize the value of AI in healthcare. For Nairobi's hospitals, insights from other industries may inform regulatory compliance, algorithm transparency, and workforce training strategies, aligning with broader performance goals.

AI implementation in healthcare faces systemic challenges that can hinder its effectiveness. These include inadequate infrastructure, lack of technical expertise, limited funding, and cultural resistance to digital systems. In Nairobi's Public hospitals, barriers such as unreliable internet connectivity and low digital literacy among staff complicate the integration of AI into workflows. Data quality and availability are also persistent issues. AI models require accurate and diverse datasets to function effectively, yet many Kenyan health facilities lack digitized health records. Furthermore, algorithmic bias and a lack of contextual adaptability may result in skewed predictions that are not representative of the local population. Ethical concerns, such as data privacy and informed consent, complicate the use of AI in clinical environments. Ensuring fairness and accountability in AI-driven decisions remains a significant challenge for Kenyan health institutions as they strive to adopt global standards (Harasimiuk & Braun, 2022).

AI adoption serves as a driver of innovation across Kenya's business landscape, with notable effects in the healthcare sector. In medical diagnostics, AI supports more accurate imaging interpretations and personalized treatments tailored to patient profiles (Pantserev, 2020). These innovations reduce misdiagnoses and support preventive care, enhancing overall performance in public hospitals. AI tools also catalyze innovation in service delivery. Chatbots and virtual assistants provide 24/7 access to health information, improving service accessibility. Predictive tools guide stock management and clinical decision-making, streamlining operations and reducing waste (Gerke et al., 2020). Across sectors, AI fosters continuous improvement and responsiveness to market demands. Organizations embracing AI report higher innovation rates, faster deployment of new services, and improved adaptability to emerging public health needs.

Kenya's regulatory environment presents both challenges and opportunities for the utilization of AI in healthcare. The Data Protection Act and emerging digital policies require hospitals to secure sensitive patient data and uphold ethical use of AI technologies (Kenya Government, 2023). Compliance with such regulations ensures accountability but also imposes significant structural and procedural requirements. According to Harasimiuk and Braun (2022), the absence of tailored AI regulations creates uncertainty that hinders investment in AI systems. Ethical issues, such as algorithmic transparency, bias prevention, and equitable access, require formalized frameworks to support the safe and inclusive implementation of these systems. Healthcare institutions must invest in internal governance structures, such as ethics committees and AI oversight boards, to align with emerging standards and regulations. By establishing compliance pathways, Nairobi's Public hospitals can build trust, secure stakeholder buy-in, and improve AI deployment success rates.

Regulatory clarity can positively influence AI adoption by mitigating legal and reputational risks. Donnelly (2022) asserts that organizations operating within well-defined regulatory environments exhibit greater confidence in leveraging AI solutions. In Kenya, the development of health-specific AI policies would offer hospitals a framework to innovate safely and responsibly. Clear guidelines promote transparency, encourage investment in secure technologies, and provide benchmarks for the ethical implementation of these technologies. As policymakers refine national digital health strategies, the role of public-private partnerships becomes crucial in shaping AI standards that reflect local health system realities.

Research Methodology

This study employed a descriptive correlational research. The study area is Nairobi City County, the capital of Kenya, with a specific focus on Level 5 and 6 hospitals within the county. The target population includes 210 healthcare professionals, administrators, and technical staff involved in

Artificial Intelligence and Information Technology systems across these hospitals. This group comprises physicians, nurses, IT specialists, and hospital administrators engaging with AI technologies in clinical and operational settings. To evaluate the government's efforts to enhance Universal Health Coverage (UHC) through mobile health (mHealth), the study consulted a representative from the Kenya Medical Practitioners and Dentists Union (KMPDU). Additionally, policymakers within the Ministry of Health (MOH) were engaged to assess the technological, regulatory, and legal frameworks needed to support AI-enabled self-diagnosis solutions. A stratified random sample method was employed. The study employed Yamane's sampling technique to derive a sample of 138 respondents. Primary data for this study was collected through structured questionnaires. Quantitative data obtained from the surveys was evaluated utilizing statistical software, which is the Statistical Package for the Social Sciences (SPSS). Descriptive statistics were used to summarize the data, and inferential statistics, including correlation and regression analysis, were applied to examine relationships between Artificial Intelligence adoption and healthcare performance metrics.

Effect of the Adoption Rate of AI

Descriptive Statistics

Table 1: Descriptive Statistics for AI Adoption Rate

Statement	N	Mean	Std Dev
AI adoption has improved diagnostic accuracy in our facility	115	4.12	0.83
Healthcare staff are adequately trained to use AI technologies	115	3.45	1.02
The facility has invested sufficiently in AI infrastructure	115	3.58	1.15
AI adoption has reduced patient waiting times	115	3.95	0.87
Data privacy concerns hinder AI adoption in our facility	115	3.72	1.09
There is resistance to AI adoption among healthcare staff	115	3.49	1.18
The facility has adequate budget allocation for AI adoption	115	3.67	1.21
AI adoption has improved staff productivity in our facility	115	4.05	0.91
Management strongly supports AI adoption initiatives	115	3.89	0.96
The pace of AI adoption in our facility is satisfactory	115	3.52	1.08
AI adoption has enhanced our facility's competitive advantage	115	3.78	1.03
There are sufficient AI vendor support services available	115	3.41	1.14

The descriptive statistics for AI adoption rate indicate that respondents generally agree that AI has improved diagnostic accuracy in their facilities (Mean = 4.12, SD = 0.83), representing the highest-rated item in this category. Respondents also reported strong agreement that AI adoption has improved staff productivity (Mean = 4.05, SD = 0.91), and that it has contributed to reduced patient waiting times (Mean = 3.95, SD = 0.87). Additionally, management support for AI adoption initiatives received positive ratings (Mean = 3.89, SD = 0.96), while respondents acknowledged that AI adoption has enhanced their facility's competitive advantage (Mean = 3.78, SD = 1.03).

However, notable challenges persist, including data privacy concerns (Mean = 3.72, SD = 1.09) and staff resistance to AI adoption (Mean = 3.49, SD = 1.18). Budget allocation for AI adoption

Journal of Business and Strategic Management
ISSN 2520-0402 (online)
Vol. 10, Issue No. 13, pp. 31 - 52, 2025 www.carijournals

received moderate ratings (Mean = 3.67, SD = 1.21), suggesting mixed perceptions about financial resource adequacy. The relatively lower scores for staff training adequacy (Mean = 3.45, SD = 1.02), the pace of AI adoption (Mean = 3.52, SD = 1.08), and availability of vendor support services (Mean = 3.41, SD = 1.14) suggest potential areas for improvement in the implementation of AI technologies in healthcare facilities. These findings emphasize that while AI is perceived as beneficial for efficiency, productivity, and accuracy, its full impact may be hindered by organizational readiness factors such as training, infrastructure, vendor support, and change resistance. The strong management support and recognized competitive advantages indicate positive organizational commitment, yet implementation gaps can influence the overall effectiveness of AI adoption.

Correlation of AI Adoption Rate and Healthcare Performance

Table 2: Correlation Analysis between AI Adoption Rate and Healthcare Performance

Variables	AI Adoption Rate	Healthcare Performance
AI Adoption Rate	1.000	0.646**
Healthcare Performance	0.646**	1.000

Note: ** Correlation is significant at the 0.01 level (2-tailed) N = 115

The correlation analysis reveals a strong positive correlation between AI Adoption Rate and Healthcare Performance ($r = 0.646$, $p < 0.01$). This indicates that as AI adoption rates increase in healthcare facilities, there is a corresponding significant improvement in healthcare performance outcomes. This suggests a meaningful real-world link between how extensively AI is adopted and the perceived improvement in service delivery outcomes. It highlights AI as not just a technological shift but a performance-enhancing tool in healthcare contexts. The correlation coefficient of 0.646 suggests a substantial relationship, indicating that approximately 64.6% of the linear relationship between these variables is explained by their association.

Linear Regression between AI Adoption Rate and Healthcare Performance

Model Summary

Table 3: Model Summary of AI Adoption Rate and Healthcare Performance

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Sig. F Change
1	0.646	0.417	0.412	0.45429	0.000

Predictors: (Constant), AI Adoption Rate

The regression analysis examining the relationship between AI Adoption Rate and Healthcare Performance yielded significant results. The model summary indicates that AI Adoption Rate explains a substantial proportion of variance in Healthcare Performance ($R^2 = 0.417$). This suggests that 41.7% of the variation in Healthcare Performance can be attributed to AI Adoption Rate. The relationship between the variables was strong and positive ($R = 0.646$), indicating that changes in AI Adoption Rate are associated with corresponding changes in Healthcare Performance. This reinforces the strategic importance of AI investment, as nearly half of performance variation can be explained by AI-related changes, validating its role in healthcare modernization.

ANOVA Table for AI Adoption Rate and Healthcare Performance

Table 4: ANOVA of AI Adoption Rate and Healthcare Performance

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	6.952	1	6.952	80.646	0.000
Residual	9.741	113	0.086		
Total	16.693	114			

Dependent Variable: Healthcare Performance Predictors: (Constant), AI Adoption Rate

The analysis of variance was conducted to examine the relationship between AI Adoption Rate and Healthcare Performance. The results revealed a statistically significant effect of AI Adoption Rate on Healthcare Performance, $F(1, 113) = 80.646$, $p < 0.001$. This indicates that the variation in Healthcare Performance explained by AI Adoption Rate is significantly greater than what would be expected by chance alone. The model's sum of squares regression (6.952) compared to the total sum of squares (16.693) suggests that a substantial portion of the variance in Healthcare Performance can be attributed to AI Adoption Rate. These results confirm that the observed improvements in healthcare performance are statistically linked to AI adoption rather than random chance, strengthening the reliability of the model.

Regression Coefficients for Linear Regression between AI Adoption Rate and Healthcare Performance

Table 5: Coefficients of AI Adoption Rate and Healthcare Performance

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.600	0.300		5.333	0.000
AI Adoption Rate	0.600	0.100	0.646	6.000	0.000

The regression analysis examining the relationship between AI Adoption Rate and Healthcare Performance yielded significant results. The coefficients table revealed that AI Adoption Rate was a significant predictor of Healthcare Performance ($\beta = 0.646$, $t = 6.000$, $p < 0.001$). The unstandardized coefficient ($B = 0.600$, $SE = 0.100$) indicates that for every one-unit increase in AI Adoption Rate, there is a corresponding 0.600 unit increase in Healthcare Performance. The constant term ($B = 1.600$, $SE = 0.300$) represents the expected Healthcare Performance when AI Adoption Rate is zero. This implies that healthcare organizations can expect tangible gains in performance for every incremental improvement in AI integration, offering a clear justification for continued investment and upskilling in AI technologies.

Challenges in AI Technology Adoption

The open-ended responses revealed financial constraints, technical infrastructure limitations, staff resistance, and training inadequacies as primary barriers to AI adoption. One respondent indicated that *"the initial cost of acquiring AI systems is prohibitive for our facility, especially when considering the need for hardware upgrades and software licensing fees."* Technical challenges were prominent, with a senior IT officer stating that *"our existing network infrastructure cannot handle the data processing requirements of AI systems, leading to frequent system crashes."* Staff resistance emerged as significant organizational hurdles, with a medical officer noting that *"many of our senior staff members are skeptical about AI capabilities and prefer traditional methods, creating resistance to change initiatives."* Training inadequacies compounded these challenges, as a nursing supervisor explained that *"the training provided was insufficient, and staff feel unprepared to use AI systems effectively in their daily work."*

Effect of Integration of AI on the Performance of the Healthcare Sector

Descriptive Statistics

Table 6: Descriptive Statistics for AI Integration

Statement	N	Mean	Standard Deviation
AI integration has improved resource allocation	115	3.82	0.92
AI systems are well-integrated with existing healthcare processes	115	3.56	1.05
Integration of AI has improved operational efficiency	115	3.94	0.89
Staff find integrated AI systems easy to use	115	3.38	1.12
AI integration has improved patient care quality	115	4.05	0.84
Technical support for AI systems is readily available	115	3.25	1.18
AI integration has reduced system downtime in our facility	115	3.71	1.01
Data compatibility between AI and existing systems is excellent	115	3.47	1.09
AI integration has improved communication between departments	115	3.85	0.95
Integrated AI systems have enhanced clinical decision making	115	3.98	0.87
Staff are satisfied with the user interface of integrated AI systems	115	3.29	1.16
AI integration has improved patient data management processes	115	3.91	0.93

The descriptive statistics for AI integration reveal that respondents strongly agree that AI integration has had the most notable impact on improving patient care quality (Mean = 4.05, SD = 0.84), enhancing clinical decision making (Mean = 3.98, SD = 0.87), and improving operational efficiency (Mean = 3.94, SD = 0.89). Additional positive outcomes include improved patient data management processes (Mean = 3.91, SD = 0.93) and enhanced communication between departments (Mean = 3.85, SD = 0.95). There is also agreement that AI integration has improved resource allocation (Mean = 3.82, SD = 0.92) and reduced system downtime (Mean = 3.71, SD = 1.01). However, respondents reported lower scores for staff satisfaction with user interfaces of integrated AI systems (Mean = 3.29, SD = 1.16), availability of technical support (Mean = 3.25, SD = 1.18), and ease of use for staff (Mean = 3.38, SD = 1.12). Data compatibility between AI and existing systems also received moderate ratings (Mean = 3.47, SD = 1.09), while the overall integration with existing healthcare processes scored moderately (Mean = 3.56, SD = 1.05), indicating that user adoption and technical integration remain pain points within the healthcare systems. These areas present opportunities for future investments and trainings and system design investments.

Correlation of AI Integration and Healthcare Performance

Table 7: Correlation Analysis between AI Integration and Healthcare Performance

Variables	AI Integration	Healthcare Performance
AI Integration	1.000	0.657**
Healthcare Performance	0.657**	1.000

Note: ** Correlation is significant at the 0.01 level (2-tailed) N = 115

The correlation analysis demonstrates a strong positive correlation between AI Integration and Healthcare Performance ($r = 0.657$, $p < 0.01$). This indicates that as AI integration levels increase in healthcare facilities, there is a corresponding and statistically significant improvement in healthcare performance outcomes. This is the highest correlation among all the AI dimensions evaluated, emphasizing that integration is not merely a supportive component, but a core driver of systemic improvement. Effective integration likely enhances coordination of care, reduces redundancy, and facilitates faster decision-making.

Linear Regression between AI Integration and Healthcare Performance

Model Summary

Table 8: Model Summary of AI Integration and Healthcare Performance

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Sig. F Change
1	0.657	0.431	0.426	0.4559	0.000

Predictors: (Constant), AI Integration

The regression analysis confirms that AI Integration explains a substantial proportion of variance in Healthcare Performance ($R^2 = 0.431$). This suggests that 43.1% of the variation in Healthcare Performance can be attributed to AI Integration. The relationship between the variables was strong and positive ($R = 0.657$), indicating that changes in AI Integration are associated with corresponding changes in Healthcare Performance.

ANOVA Table for AI Integration and Healthcare Performance

Table 9: ANOVA of AI Integration and Healthcare Performance

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	7.171	1	7.171	85.604	0.000
Residual	9.466	113	0.084		
Total	16.637	114			

Dependent Variable: Healthcare Performance Predictors: (Constant), AI Integration

The ANOVA results further validate the regression model. The F-statistic value ($F = 85.604$, $p < 0.001$) confirms that the model significantly predicts Healthcare Performance. This high F-value indicates that AI Integration contributes meaningfully to performance improvement**.** The model's sum of squares regression (7.171) compared to the total sum of squares (16.637) suggests that a substantial portion of the variance in Healthcare Performance can be attributed to AI Integration.

Regression Coefficients for Linear Regression between AI Integration and Healthcare Performance

Table 10: Coefficients of AI Integration and Healthcare Performance

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.500	0.300		5.000	0.000
AI Integration	0.655	0.112	0.657	5.871	0.000

The coefficients table revealed that AI Integration was a significant predictor of Healthcare Performance ($\beta = 0.657$, $t = 5.871$, $p < 0.001$). The unstandardized coefficient ($B = 0.655$, $SE = 0.112$) indicates that for every one-unit increase in AI Integration, there is a corresponding 0.655 unit increase in Healthcare Performance. The constant term ($B = 1.500$, $SE = 0.300$) represents the expected Healthcare Performance when AI Integration is zero. This substantial coefficient highlights the operational value of integration — indicating that AI-related upgrades are not just technical improvements, but major contributors to service delivery outcomes. The strength of this relationship justifies increased policy focus and resource allocation toward integrated AI systems, especially in institutions struggling with inefficiencies or service quality challenges.

Impact of AI Integration on Daily Workflow

Responses revealed both positive transformations and adaptation challenges in workflow management following AI integration. A radiologist indicated that *"AI-assisted diagnostic imaging has reduced the time needed for scan interpretation by approximately 40%, allowing us to handle more patients daily."* Enhanced decision-making was frequently mentioned, as an emergency physician stated that *"AI-powered clinical decision support systems have improved our diagnostic*

Journal of Business and Strategic Management
ISSN 2520-0402 (online)
Vol. 10, Issue No. 13, pp. 31 - 52, 2025
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accuracy, particularly in identifying critical conditions during busy periods." However, adaptation challenges were acknowledged, with a senior physician observing that *"the initial period of AI integration disrupted our established workflows, requiring significant adjustments in patient scheduling."* A medical records officer noted that *"adapting to new AI interfaces required considerable time and effort, initially reducing productivity as staff learned to navigate the systems effectively."*

Utilization of AI in Predicting Emerging Diseases on Healthcare Performance
Descriptive Statistics

Table 11: Descriptive Statistics for AI Utilization in Disease Prediction

Statement	N	Mean	Standard Deviation
AI accurately predicts disease outbreaks	115	3.75	0.97
AI predictions help in resource planning	115	3.88	0.91
Disease prediction capabilities are regularly utilized	115	3.42	1.08
Staff trust AI-generated disease predictions	115	3.28	1.15
AI predictions have improved preventive care	115	3.84	0.94
Disease prediction has reduced healthcare costs	115	3.65	1.02
AI disease prediction has improved early warning systems	115	3.79	0.98
Disease prediction capabilities enhance staff preparedness	115	3.73	1.01
AI predictions have reduced response time to disease outbreaks	115	3.67	1.05
Disease prediction has improved patient screening processes	115	3.81	0.96
AI predictions are valuable for epidemic surveillance	115	3.92	0.89
Disease prediction capabilities support infection control measures	115	3.76	0.99

The descriptive statistics for AI utilization in disease prediction show that respondents most strongly agree that AI predictions are valuable for epidemic surveillance (Mean = 3.92, SD = 0.89), followed by agreement that AI predictions help in strategic resource planning (Mean = 3.88, SD = 0.91) and have improved the delivery of preventive care (Mean = 3.84, SD = 0.94). Additional positive impacts include improved patient screening processes (Mean = 3.81, SD = 0.96) and enhanced early warning systems (Mean = 3.79, SD = 0.98). There is also agreement that AI disease prediction capabilities support infection control measures (Mean = 3.76, SD = 0.99), accurately predict disease outbreaks (Mean = 3.75, SD = 0.97), and enhance staff preparedness (Mean = 3.73, SD = 1.01). Furthermore, respondents acknowledged that AI predictions have reduced response time to disease outbreaks (Mean = 3.67, SD = 1.05) and healthcare costs (Mean = 3.65, SD = 1.02).

However, lower scores were reported for regular utilization of disease prediction capabilities (Mean = 3.42, SD = 1.08) and staff trust in AI-generated predictions (Mean = 3.28, SD = 1.15), highlighting the need for greater staff sensitization and support systems to increase trust and utilization. This indicates that while the technological capabilities exist, human and organizational factors may limit full adoption.

Correlation of AI Utilization in Disease Prediction and Healthcare Performance

Table 12: Correlation Analysis between AI Utilization for Disease Prediction and Healthcare Performance

Variables	AI Utilization for Disease Prediction	Healthcare Performance
AI Utilization for Disease Prediction	1.000	0.668**
Healthcare Performance	0.668**	1.000

Note: ** Correlation is significant at the 0.01 level (2-tailed) N = 115

The correlation analysis reveals the strongest positive correlation among all AI dimensions between AI Utilization for Disease Prediction and Healthcare Performance ($r = 0.668$, $p < 0.01$). This strong association implies that predictive technologies serve as key drivers of preparedness and efficiency within the sector. The correlation coefficient of 0.668 represents the highest relationship strength, suggesting that predictive capabilities in disease management are the most influential AI application for healthcare performance enhancement.

Linear Regression between AI Utilization in Disease Prediction and Healthcare Performance

Model Summary

Table 13: Model Summary of AI Utilization for Disease Prediction and Healthcare Performance

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Sig. F Change
1	0.668	0.446	0.441	0.4569	0.000

Predictors: (Constant), AI Utilization for Disease Prediction

The model summary indicates that AI Utilization for Disease Prediction explains a substantial proportion of variance in Healthcare Performance ($R^2 = 0.446$). This suggests that 44.6% of the variation in Healthcare Performance can be attributed to AI Utilization for Disease Prediction factors. A high R value of 0.668 further reinforces this, pointing to a stable and meaningful association.

ANOVA Table for AI Utilization in Disease Prediction and Healthcare Performance

Table 14: ANOVA of AI Utilization for Disease Prediction and Healthcare Performance

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	7.422	1	7.422	91.168	0.000
Residual	9.215	113	0.082		
Total	16.637	114			

Journal of Business and Strategic Management
ISSN 2520-0402 (online)
Vol. 10, Issue No. 13, pp. 31 - 52, 2025
www.carijournals

Dependent Variable: Healthcare Performance Predictors: (Constant), AI Utilization for Disease Prediction

The ANOVA results confirm the model's significance (F = 91.168, $p < 0.001$), supporting the conclusion that the effect of AI utilization in disease prediction on healthcare performance is not random but consistent and measurable. This highlights the value of predictive systems in clinical and administrative planning, particularly in environments prone to outbreaks or resource constraints.

Regression Coefficients for Linear Regression between AI Utilization in Disease Prediction and Healthcare Performance

Table 15: Coefficients of AI Utilization for Disease Prediction and Healthcare Performance

Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	Std. Error	Beta		
(Constant)	1.500	0.300		5.000	0.000
AI Utilization for Disease Prediction	0.645	0.108	0.668	5.965	0.000

The coefficients table revealed that AI Utilization for Disease Prediction was a significant predictor of Healthcare Performance ($\beta = 0.668$, t = 5.965, $p < 0.001$). The unstandardized coefficient (B = 0.645, SE = 0.108) indicates that for every one-unit increase in AI Utilization for Disease Prediction, there is a corresponding 0.645 unit increase in Healthcare Performance. The constant term (B = 1.500, SE = 0.300) represents the expected Healthcare Performance when AI Utilization for Disease Prediction is zero. This consistent improvement supports the growing role of anticipatory systems in modern health management.

AI Disease Prediction Impact on Outbreak Management

Responses demonstrated significant appreciation for AI's predictive capabilities while revealing trust and utilization challenges. An epidemiologist indicated that "AI prediction models have enabled us to identify potential outbreak patterns 2-3 weeks earlier than traditional surveillance methods, giving us crucial preparation time." Resource planning improvements were noted, with a hospital administrator stating that "AI predictions help us anticipate medication and supply needs during potential outbreaks, reducing stockouts and ensuring adequate preparation." However, trust issues were prominent, with a senior physician indicating that "while the predictions are often accurate, some staff members remain skeptical about relying on AI for critical decisions, preferring to wait for traditional confirmation." Technical limitations were mentioned, as a data analyst stated that "the complexity of AI prediction reports sometimes makes it difficult for non-technical staff to understand and act upon the recommendations effectively."

Observed Changes in Healthcare Performance

Responses revealed comprehensive performance improvements with quantifiable impacts on service delivery and patient outcomes. A patient relations officer indicated that "patient satisfaction scores have increased from 72% to 89% since AI implementation, primarily due to reduced waiting times and more accurate diagnoses." Clinical improvements were documented, with a quality assurance manager stating that "diagnostic accuracy rates improved from 85% to 94% in our radiology department after implementing AI-assisted imaging analysis." Operational efficiency gains were reported, with a hospital operations manager noting that "average patient processing time reduced from 4.5 hours to 2.8 hours, enabling us to serve 35% more patients daily." A risk management officer highlighted safety improvements, noting that "medication errors decreased by 52% following AI implementation in our pharmacy systems."

Conclusion

The study conclusively demonstrates healthcare facilities that actively adopt AI technologies experience substantial improvements in diagnostic accuracy, staff productivity, and patient care delivery. In addition, seamless AI integration with existing healthcare processes creates superior performance outcomes compared to standalone AI implementations. The use of AI in predicting emerging diseases delivers the highest performance value among all assessed dimensions. Epidemic surveillance capabilities, resource planning support, and preventive care improvements validate AI's superior predictive capabilities. Enhanced patient screening processes, improved early warning systems, and infection control support measures further demonstrate the comprehensive benefits of predictive AI utilization. Thus, while AI demonstrates exceptional predictive accuracy and comprehensive operational benefits, organizational barriers and staff trust issues limit optimal utilization. Healthcare facilities that overcome these barriers and fully leverage AI's predictive capabilities achieve the greatest performance improvements.

Recommendations

Healthcare facilities should establish comprehensive staff training programs to address the training inadequacies identified in the study. Additionally, improving system usability should be a central consideration during AI integration. Given the significant impact of clinical decision-making enhancements identified in the study, integration strategies should prioritize decision support tools that seamlessly embed into existing clinical processes. To improve staff trust in AI-based disease prediction tools, healthcare organizations should promote transparency through mechanisms that explain AI-generated predictions, monitor accuracy, and educate staff on the logic underpinning AI decisions. In response to challenges related to cost reduction, healthcare facilities are encouraged to develop financial strategies that reflect both the immediate costs and delayed benefits of AI implementation.

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