Strategic Integration of Artificial Intelligence in Healthcare: Theoretical Frameworks, Adoption, Enablers, and Barriers — A Scoping Review

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Abstract

Background
Healthcare organizations increasingly leverage Artificial Intelligence (AI) to enhance clinical decision-making, operational efficiency, and strategic positioning. However, existing research on human-AI collaboration in healthcare has not fully explored how strategic management theories intersect with user-centered design principles, interpretability, and ethical considerations essential for building reliable AI partners.

Objectives
This scoping review aimed to (i) map the current landscape of AI-enabled knowledge sharing in healthcare organizations; (ii) identify theoretical frameworks, including human-in-the-loop and user acceptance models; (iii) examine both organizational and user-level enablers and barriers, and (iv) propose an integrated strategic management perspective for more robust, inclusive, and ethically grounded AI adoption.

Eligibility Criteria
Eligible studies addressed AI-enabled interventions (e.g., machine learning, deep learning, natural language processing) in diverse healthcare settings (resource-limited, public, and private institutions), with no date restrictions. Only English-language publications were included.

Sources of Evidence and Charting Methods
A comprehensive search across SCOPUS, PubMed, and EBSCOhost-Web of Science yielded 327 articles, with 297 screened for relevance using Covidence software. Five studies met eligibility criteria and were thematically synthesized using NVivo. Analytical categories spanned organizational readiness, stakeholder acceptance, digital/ethical infrastructure, and collaborative AI design features.

Results
Key facilitators of successful AI adoption included leadership endorsement, specialized training, robust institutional support, and perceived utility of AI solutions. Frequently employed frameworks (Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology, Diffusion of Innovations, Sociotechnical Systems) addressed individual-level behaviors but rarely accounted for deeper strategic management factors. Ethical concerns related to patient privacy, data security, and algorithmic bias underscored the need for transparent and explainable AI, particularly in high-stakes healthcare contexts.

Conclusions
Current research on healthcare AI adoption predominantly emphasizes user acceptance without fully integrating strategic management and collaborative design principles. Future inquiry should incorporate human-in-the-loop approaches, interpretability methodologies, and strategic management theories to enhance AI sustainability and transparency, foster trust, and safeguard ethical standards. By coupling these dimensions with organizational strategy, healthcare systems can more effectively harness AI for sustainable competitive advantage, elevated clinical outcomes, and responsible innovation.

1. Introduction

1.1 Background and Rationale

Artificial Intelligence (AI) has rapidly evolved from a novel concept into a transformative driver within healthcare systems, promising enhancements in diagnostic accuracy, clinical decision-support, and operational management (2,3). In select high-resource or commercial environments, AI-driven tools particularly those employing deep learning or predictive analytics have matched or even surpassed human performance, notably in radiology interpretation and infectious disease surveillance (4,5). However, much of this evidence originates from settings with ample technological infrastructure and financial backing (6) leaving a critical knowledge gap regarding AI's impact and feasibility in low-resource, community-based, or non-profit healthcare organizations (7,8).

This gap is exacerbated by uncertain donor landscapes. Agencies such as USAID and international non-governmental organizations frequently adjust or withdraw funding, restricting the development of robust data infrastructures and digital upskilling programs that underpin successful AI deployment (9–11). Consequently, organizations under resource constraints often lack the requisite tools to cultivate human-AI collaboration one that integrates user-centered design principles, transparent decision-making processes, and equitable access to AI-driven insights (12). Weakened resource inflows can further hinder the development of robust data infrastructures and comprehensive digital training for healthcare personnel (13) Against this backdrop, there is growing interest in harnessing AI to sustain and enhance collaborative decision-making and operational workflows in contexts that receive minimal external support (14).

To map how AI may function as a strategic asset for knowledge sharing, collaborative decision-making, and workflow optimization in these environments, this study employs a Scoping Review methodology. Scoping reviews systematically map the existing literature (including grey literature) on a topic to identify key concepts, research gaps, and evidence types. This paper illuminates how AI adoption can enhance organizational learning, resource mobilization, and long-term strategic alignment particularly in resource-scarce settings.

1.2 Problem Statement and Objectives

Despite extensive scholarship on AI's clinical applications and algorithmic performance, there remains a paucity of studies examining how AI-driven solutions can be effectively tailored for, and sustained within, non-profit and community-based organizations experiencing diminished donor support (15) . Most research emphasizes clinical endpoints or the technical intricacies of AI models, often overlooking the interplay of user factors such as digital literacy, institutional leadership, and organizational culture and how these factors collectively shape collaborative knowledge sharing, workforce capacity-building, and strategic alignment (16,17). This omission is especially consequential for non-profit entities, which confront unique governance structures, heightened accountability standards, and persistent funding volatility(15).

Hence, this scoping review systematically charts the existing literature on AI adoption, utilization, and advanced computational methods in healthcare contexts burdened by resource limitations, with a particular focus on uncovering which theoretical frameworks especially those grounded in strategic management have been employed to guide or explain these implementations.
Particular attention is paid to how AI can bolster knowledge exchange, streamline organizational processes, and enrich decision-making in environments where donor support has declined. By leveraging a multi-theoretical framework, this review aims to elucidate the pathways through which AI fosters sustainable advantage, collaborative intelligence, and enhanced equity in healthcare outcomes (18).

The review objectives development was guided by the **SPIDER framework** (Sample, Phenomenon of Interest, Design, Evaluation, Research type), which offers a broader lens for capturing the organizational, strategic, and human-centered factors inherent to AI deployment in diverse healthcare contexts.

The **Sample** comprised healthcare organizations both non-profit and for-profit facing resource limitations, including insufficient funding or infrastructure. The **Phenomenon of Interest** involved the adoption and utilization of advanced computational techniques such as AI, machine learning, deep learning, and natural language processing to enhance knowledge management, organizational processes, or strategic decision-making. **Design** encompassed all empirical approaches (qualitative, quantitative, and mixed methods), as well as conceptual or framework-oriented works. **Evaluation** focused on outcomes related to knowledge sharing, workflow optimization, stakeholder engagement, and alignment with strategic management goals. The **Research type** category accommodated a wide array of sources, including peer-reviewed articles, grey literature, and policy documents, ensuring a comprehensive examination of how AI technologies are implemented and assessed in resource-limited healthcare settings.

Objectives

1. **To systematically map** the existing body of evidence on AI adoption and utilization in resource-constrained healthcare organizations.

2. **To identify** the theoretical frameworks employed in studies of AI adoption within healthcare, critically examining their relevance to strategic management practices and human-AI collaboration (e.g., technology acceptance models, sociotechnical systems, dynamic capabilities).
3. **To analyze** barriers and enablers influencing AI adoption in healthcare contexts, proposing strategic management insights and highlighting theoretical gaps. The goal is to offer future research directions that address user-centered design, interpretability, and ethical dimensions of AI-driven health services.

By centering on these objectives, this scoping review contributes to the broader discourse on designing and deploying collaborative AI systems that reflect not only algorithmic sophistication but also the complex realities of healthcare organizations operating under significant resource constraints.

3.0 Methodology (Scoping Review Approach)

A scoping review framework was employed to systematically identify and synthesize evidence on AI adoption in healthcare organizations operating under constrained resources. The protocol for this review, which adheres to established guidelines (13–15), was registered on the Open Science Framework (OSF) at https://osf.io/preprints/socarxiv/39f7r_v1 (DOI 10.17605/OSF.IO/CM2B5). Registration ensures methodological transparency, enabling replication or further refinement of this procedure.

Three electronic databases namely; SCOPUS, PubMed, and EBSCOhost (Web of Science) were systematically searched using a structured strategy designed to capture literature intersecting AI, knowledge-sharing processes, and theories of strategic management. An initial total of 327 records was retrieved (SCOPUS n=93, PubMed n=200, EBSCOhost n=34). After 29 duplicates were removed, 298 unique records underwent title and abstract screening in Covidence software.

Three reviewers independently assessed each record for relevance, resolving disagreements through discussion or by consulting a third-party adjudicator. Thirteen studies progressed to full-text review, with eight meeting inclusion criteria. Owing to inaccessibility due to paywalls or institutional restrictions on three full-text documents, five articles were ultimately selected for data extraction and synthesis.
Data was charted using a structured template in Covidence derived from the SPIDER components, adapted to incorporate strategic management variables (e.g., leadership, organizational readiness, resource allocation, and theoretical frameworks). This approach allowed for a nuanced capture of study design, AI techniques, implementation processes, and indicators of success or barriers. The extracted data was imported into NVivo software for a qualitative thematic analysis, illuminating patterns in AI-related knowledge sharing, workflow optimization, user-centered engagement, and ethical dimensions critical to healthcare organizations with constrained resources. Emphasizing SPIDER ensured the review retained its breadth in capturing both empirical and conceptual works, thereby unveiling multifaceted insights into how AI might be harnessed collaboratively to improve decision-making and operational efficiencies in settings where resources remain limited.

4.0 Results

The five studies employed a range of methodological designs, including two qualitative explorations with interpretive interviews, one mixed-methods investigation combining surveys and interviews, one conceptual paper proposing a theoretical framework, and one study focused on framework development and evaluation. Geographic contexts spanned Europe (Wales), the Middle East (Jordan), the United States, and Sub-Saharan Africa (Botswana and Tanzania). While participant samples varied, most involved healthcare professionals, general practitioners, nurses, and specialists or organizational leaders tasked with implementing or supervising AI solutions. One conceptual study did not include direct data collection but synthesized secondary literature to offer theoretical insights. Collectively, these sources emphasized how organizational readiness, leadership commitment, training programs, and perceived usefulness shape AI adoption in settings constrained by funding or infrastructural limitations. They further underscored the significance of aligning AI initiatives with ethical obligations, transparent processes, and interpretability features, particularly when multiple stakeholders are engaged and resources are scarce(6,7,19).

5.0 Analysis

5.1 Thematic Analysis

A synthesis of the five retained studies reveals seven interlocking themes that together explain not merely *whether* AI is adopted in resource-constrained healthcare, but *how* it becomes a sustainable, equitable, and ethically defensible organizational asset. Each theme is explicitly linked to strategic-management constructs (dynamic capabilities, resource-based view) and user-centred informatics theory (TAM/UTAUT2, sociotechnical systems).

5.1.1 AI Adoption and Utilization

Adoption patterns varied considerably across healthcare specialties and organizational contexts. Certain specialties such as radiology and cardiology exhibited a more favorable disposition toward AI tools, attributable to the routine use of technology-enhanced diagnostic systems (7,8). In contrast, practitioners in general medicine and nursing demonstrated more conservative attitudes, often influenced by perceptions of limited infrastructure or unfamiliarity with advanced computational methods (8). Organizational readiness consistently emerged as a decisive factor in determining the pace and extent of AI adoption. Evidence from Tanzania and Botswana underscored how inadequate digital infrastructure and weak managerial advocacy impede successful integration, highlighting broader gaps in strategic alignment and technological capability (7,19).

Acceptance among healthcare stakeholders was equally pivotal. Qualitative inquiries indicated that confidence in AI's utility, perceived ease of use, and trust in the technology underpinned successful uptake (8). Conceptual models rooted in user acceptance frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) reinforced the importance of perceived usefulness, effort expectancy, and social influence (6).

Regarding **utilization,** AI contributed to notable gains in clinical decision-making, particularly through enhancements in diagnostic precision, predictive modeling, and outbreak surveillance (8,20) The EventEpi framework, for instance, leveraged natural language processing to improve public health surveillance by detecting disease outbreaks more accurately and expediently (20) Operational efficiencies also benefited from AI-driven interventions, which automated routine tasks and reduced administrative workloads (7) However, the extent to which AI could be effectively integrated depended heavily on organizational competencies, the interoperability of existing systems, and sustained engagement from practitioners and leadership (19).

While these studies highlighted the operational utility of AI in healthcare, there remained a marked gap in understanding AI as a strategic organizational resource. Current models primarily addressed user acceptance and technology diffusion but did not fully explore AI's role in fostering sustained competitive advantage, dynamic capabilities, or long-term resource mobilization. Equally notable was the limited engagement with themes such as robust user-centered design, explainable AI, and human-in-the-loop frameworks that are integral to ensuring interpretability, ethical alignment, and genuinely collaborative AI in resource-constrained healthcare contexts.

5.1.2 Organizational Readiness, Governance & Strategic Alignment

Leadership endorsement, clear accountability structures, and alignment with institutional strategy consistently differentiated successful from stalled implementations. In Tanzanian primary-care facilities, weak managerial advocacy and diffuse responsibility slowed electronic health-record (EHR) roll-out (18). A Welsh interview study likewise found that practitioners' enthusiasm for diagnostic AI was tempered when executives did not champion the technology (20). Botswana's VisualDx pilot framed explicit governance check-points as a prerequisite for long-term uptake (6). These findings corroborate the strategic-management proposition that top-management orchestration is a dynamic capability essential for scaling AI.

5.1.3 Capacity-Building & Digital Literacy

Clinicians across Wales, Botswana, and Tanzania demanded modular, role-specific training delivered flexibly around clinical workloads (7; 6). Where structured programmes were absent, effort expectancy rose and adoption stagnated, confirming UTAUT2's facilitating-conditions construct.

5.1.4 Technical Infrastructure & Interoperability

Network instability, irregular power supply and limited API standardization surfaced as first-order constraints on scalability (18; 6). Commentaries on disability-focused AI added that high infrastructure costs and unreliable bandwidth in LMICs further compound inequities (20). Distinguishing hard infrastructure (connectivity, energy) from soft interoperability (standards, data schemas) clarifies investment priorities for policymakers.

5.1.5 Equity of Access & Geographical Disparity

Practitioners in metropolitan hubs reported greater readiness and more positive attitudes toward AI than counterparts in peripheral facilities (1). Inclusive-design commentaries warned that high development costs and sparse local datasets risk widening disability and rural–urban gaps unless equity is embedded as a design criterion (20).

5.1.6 Human Factors: Usability, Workload & Professional Autonomy

Botswana users praised VisualDx's offline mode but criticized overly broad differential lists that slowed workflow (6). Tanzanian clinicians feared EHRs might erode professional autonomy and add documentation burden (18). Addressing socio-professional identity factors is therefore vital to prevent techno-centrism from undermining adoption.

5.1.7 Risk Management & Patient-Safety Governance

Only (21) provided a systematic framework that spans hazard identification, likelihood–consequence analysis, and ISO 31000-aligned mitigation strategies for smart healthcare systems. Embedding pre-deployment safety audits and continuous monitoring would operationalize "responsible innovation" across the AI lifecycle.

5.1.8 Ethics, Inclusivity & Algorithmic Bias

Privacy breaches, non-representative training data, and inaccessible interfaces were recurring concerns, particularly in disability care (20). Recommended safeguards include algorithmic-bias audits, privacy-by-design encryption, and multimodal interaction modalities.

5.1.9 Integrated Synthesis & Strategic Implications

Collectively, the themes demonstrate that user-acceptance models explain only a fraction of AI success. Sustainable, trustworthy AI demands parallel investment in governance, human capital, resilient infrastructure, equity promotion, rigorous risk management, and inclusive design. Embedding these dimensions within organizational strategy transforms AI from pilot-stage novelty into a dynamic capability that yields competitive advantage and improved clinical outcomes in resource-limited settings.

5.2 Theoretical Frameworks

Predominantly, the reviewed studies employed technology adoption and user acceptance theories to examine the integration of AI in healthcare. Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT TAM and UTAUT) were prevalent, focusing on individual-level perceptions of usefulness and ease of use, while the Diffusion of Innovations (DOI) framework provided insights into how new technologies gain traction across organizations (6,8,19) Sociotechnical Systems theory was occasionally invoked to capture the interplay between technological implementations and social contexts, reflecting the complexity of health environments undergoing digital transitions (19).

Although these frameworks effectively dissected acceptance-related constructs such as performance expectancy and effort expectancy they fell short of addressing broader strategic management considerations. Most studies concentrated on the initial phases of AI adoption and did not sufficiently explain how, over the long term, healthcare organizations particularly those in resource-limited contexts burdened by unstable funding and infrastructural constraints can harness AI's strategic potential to bridge persistent service gaps. While advanced analytics and automated decision-support tools can alleviate the strain caused by limited clinical staff and financial resources, the absence of a clear framework for sustaining these innovations undermines their transformative potential. A more nuanced exploration of long-term resource allocation, strategic partnerships, and adaptive capacity is necessary to ensure that AI's early gains are both scalable and resilient in settings where donor support may fluctuate.

Barriers and Facilitators of AI Adoption

Several obstacles commonly impeded AI adoption in resource-constrained healthcare settings. Chief among them were low digital literacy, insufficient training opportunities, and infrastructural shortcomings, all of which reduced the likelihood that AI tools could be employed in routine practice (7,19) Financial constraints further compounded these difficulties, restricting both the acquisition of new technologies and investments in capacity-building(19). Resistance to change also materialized when stakeholders perceived AI as a threat to professional autonomy or lacked confidence in the technology's reliability (6,8) Ethical concerns such as data privacy, patient confidentiality, and secure data governance added another layer of complexity, underscoring the necessity of transparent regulatory frameworks to maintain trust and compliance (8,19).

Conversely, effective leadership, stakeholder engagement, and comprehensive training were identified as key facilitators of successful AI adoption (7,8). When organizational leaders explicitly endorsed technology-enhanced workflows and allocated sufficient resources, healthcare professionals reported higher levels of acceptance. In particular, training initiatives that built digital competencies and clarified the practical benefits of AI prompted favorable attitudes toward new solutions (7,19) Institutional support through policy frameworks and structured incentives further reinforced a culture open to technology-driven innovation (19).

5.3 Strategic Management Insights and Recommendations

Collectively, the reviewed studies emphasized that aligning AI initiatives with broader organizational strategies is essential for realizing their potential. AI-driven innovations can bolster competitive positioning and resource optimization, but only when supported by sufficient leadership commitment, strategic resource allocation, and an organizational culture receptive to technological evolution. Gaps in the literature persist particularly on empirical validations of conceptual adoption models. While frameworks like TAM, UTAUT, and integrated models combining trust theory yield valuable insights, they often lack rigorous field testing in real-world healthcare settings. This deficiency leaves important questions unanswered about how these models translate into tangible outcomes, particularly in contexts marked by funding shortfalls or infrastructural limitations.

In addition, there is a notable absence of explicit strategic management theories such as Dynamic Capabilities, Absorptive Capacity, and Knowledge-Based View in analyses of AI adoption in healthcare. Without such perspectives, it remains unclear how organizations sustain AI-driven advantages over time or cultivate an adaptive capacity to respond to emerging challenges.

Conclusion

This scoping review highlights pronounced variations in AI adoption across healthcare specialties and underscores the influence of organizational readiness, stakeholder engagement, and transparent governance structures on integration outcomes. Theoretical frameworks centered on technology acceptance effectively capture individual-level adoption decisions but offer limited guidance on the strategic potential of AI for achieving long-term gains in resource-constrained healthcare environments. The reviewed evidence points to training, leadership support, institutional policy frameworks, and clear ethical guidelines as facilitators of successful AI utilization. Yet the paucity of explicit strategic management perspectives signals a critical gap. Bridging technology adoption theories with management-oriented frameworks would generate more comprehensive insights and equip healthcare organizations to harness AI as a sustainable resource, balancing operational efficiencies with ethical mandates and collaborative, human-in-the-loop design.

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