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From theory to therapy: integrating artificial intelligence for transformative healthcare innovation

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ABSTRACT
The rapid evolution of artificial intelligence (AI) is reshaping healthcare by improving diagnostics, patient outcomes, and operational efficiency. Yet, many frameworks for AI adoption overlook the complex and iterative nature of healthcare systems. This study introduces the AI Healthcare Symbiosis Cycle (AI-HSC), a novel framework based on Dynamic Capabilities Theory, Systems Theory, and Kotter's 8-Step Change Model, conceptualising AI adoption as a continuous and adaptive process. Dynamic Capabilities Theory highlights the need for organisations to sense opportunities, seize resources, and change processes in response to AI advancements. Systems Theory focuses on optimising interdependencies within healthcare organisations, while Kotter's model ensures a structured approach to managing change. The AI-HSC aligns phases of AI integration – initiation, integration, evolution, and revolution – with Kotter's steps, promoting a systematic and scalable adoption strategy. Key recommendations include implementing pilot programs, fostering interdisciplinary coalitions, embedding AI literacy into organisational culture, and developing robust ethics and compliance frameworks. By bridging theory with practice, the AI-HSC provides actionable strategies for sustainable AI integration, addressing critical barriers and fostering continuous innovation. This research contributes to the digital change discourse, offering valuable insights for academia and healthcare practitioners.

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1. Introduction

The healthcare sector, foundational to societal well-being, is under pressure to improve service quality while addressing global challenges (Miller, 2020; Oderanti et al., 2021). Over the past two decades, a significant shift towards personalised, technology-driven care has emerged, but healthcare demands are outpacing resources due to system complexity (Aghdam et al., 2021). Even before the pandemic, the strain was evident, with hospital admissions and outpatient surgeries dropping by 7.8% and 10.6% from 2016 to 2020, despite rising chronic illness diagnoses (Oyeyemi & Scott, 2018). This reflects a mismatch in healthcare utilisation, as 20% of the population – mainly older adults and those with chronic conditions – accounts for 80% of healthcare costs, highlighting unequal spending distribution (DiBella et al., 2020). Workforce shortages further worsen the situation, with a projected shortfall of up to 160,000 physicians and nearly one million nurses needed by 2025, alongside declining numbers of clinical and imaging technologists (Halstead & Sautter, 2023). Additionally, the doubling of the elderly population by mid-century and the global rise in chronic diseases will further increase healthcare demands (Grinin et al., 2023). Chronic conditions remain the top cause of death worldwide, emphasising the need for sustainable, long-term care solutions and innovative strategies to relieve healthcare infrastructure pressures (Pereno & Eriksson, 2020).

Rapid advancements in artificial intelligence (AI) have significantly supported the expansion of healthcare, improved patient outcomes, and delivering cost-effective care (Hajkowicz et al., 2023). AI has become essential in tackling major challenges, including the COVID-19 pandemic, where it aided in early detection, virus tracking, and fast therapeutic development (Shahid et al., 2021). AI's potential extends to medical research, drug discovery, virtual consultations, rehabilitation, and administrative functions, revolutionising healthcare delivery. The future of AI in healthcare includes personalised medicine and home-based care, such as remote monitoring and AI-powered alerts for preventive healthcare (Kulkova et al., 2023). Additionally, AI is poised to play a critical role in clinical decision support by providing real-time,

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evidence-based recommendations to healthcare professionals (Carbonara et al., 2024; Pannunzio et al., 2023). While AI offers promising advancements in healthcare, it is essential to acknowledge the potential concerns and limitations that accompany its integration. Issues such as data privacy, algorithmic bias, and the ethical implications of AI-driven decision-making remain significant challenges. Additionally, there is often resistance among healthcare professionals, which can stem from fears of job displacement, lack of trust in AI decisions, or concerns over loss of clinical autonomy.

In this study, the term AI refers primarily to machine learning algorithms, natural language processing, and predictive analytics systems applied in clinical, diagnostic, and operational settings (Yu et al., 2018). These include both supervised and unsupervised learning models used in image interpretation, risk stratification, and workflow optimisation, as well as emerging generative AI applications such as automated clinical documentation or summarisation tools. While these technologies differ in complexity and maturity, they share common organisational challenges related to data access, interpretability, regulatory oversight, and system-wide integration (Goldhahn et al., 2018; Hosny et al., 2018). Despite increasing investments in AI across healthcare systems, implementation outcomes remain inconsistent and fragmented. Many AI initiatives are limited to isolated technical pilots or departmental tools that fail to scale or integrate into broader clinical and operational workflows (Aung et al., 2021; Bohr & Memarzadeh, 2020; Mettler et al., 2014). These shortcomings arise from a lack of structured change management, limited organisational readiness, and a lack of systemic orientation between technology and institutional processes. Previous studies on digital transformation in healthcare have noted that AI adoption often occurs in isolated, pilot-scale projects that lack formal change governance, resulting in delayed initiatives (Aung et al., 2021; Secinaro et al., 2021; Wessel et al., 2021). At the same time, research on technology integration in hospitals shows that without clear alignment between technology, clinical workflows, and governance structures, new tools struggle to achieve scale or sustainability (Mettler et al., 2014; Vial, 2019). Existing frameworks frequently conceptualise AI as a separate technical intervention rather than as a continuous, adaptive innovation integrated into a healthcare system (Mirbabaie et al., 2021). This conceptual gap highlights the need for a model that addresses strategic adaptation, organisational transformation, and systemic interdependencies that are little addressed in current literature.

Structured change management in this study refers to a methodical process for introducing, implementing, and sustaining organisational change, guided by clearly defined steps, stakeholder engagement strategies, and measurable objectives (Kotter, 1996). Such approaches provide clarity of purpose and reduce uncertainty. In contrast, unstructured approaches rely on ad hoc decision-making, fragmented leadership, and reactive adjustments. For example, an unstructured AI implementation in a radiology department may result in low clinician adoption due to lack of training and unclear benefits, even if the underlying algorithm is accurate. However, structured approaches, such as those informed by Kotter's model, have been shown to improve adoption rates of Electronic Health Records (EHRs) and digital imaging systems by coordinating stakeholder roles and aligning the change process with institutional goals (Greenhalgh & Peacock 2005; Kruse & Beane, 2018).

The rationale for developing the AI Healthcare Symbiosis Cycle (AI-HSC) is grounded in addressing the limitations observed in fragmented and static approaches to AI adoption. This study aims to conceptualise and develop a structured approach for sustainable AI integration within healthcare systems. The purpose is to bridge theoretical frameworks and practical strategies, enabling continuous and adaptive AI adoption in complex healthcare environments. The objective of this research is to formulate the AI-HSC, grounded in Kotter's 8-Step Change Model, Dynamic Capabilities Theory (Teece et al., 1997), and Systems Theory (Bertalanffy, 1969), and to propose a systematic process for embedding AI-driven innovations sustainably into healthcare practices. We pose the following research questions:

RQ1: How can AI integration in healthcare be conceptualised as a continuous and systemic innovation process rather than a one-time technological implementation?

RQ2: How do Kotter's 8 steps, Dynamic Capabilities, and Systems Theory guide design and governance of AI adoption, and which structural, ethical, and workforce conditions shape institutionalisation?

This study is structured as a systematic literature review. Following the PRISMA guidelines, it systematically identifies, selects, and analyzes peer-reviewed studies related to AI adoption in healthcare. However, the literature review in this study is designed to inform the development of a conceptual framework rather than to generate statistical generalisations. Its purpose is to identify theory-driven studies that provide insights into change management, systems thinking, and strategic adaptation in the context of AI adoption in healthcare. The approach ensures methodological rigour, transparency, and replicability, providing a comprehensive synthesis of theoretical frameworks, empirical findings, and practical insights necessary for developing the AI-HSC.

2. State-of-the-art

2.1. Clarification of the key concepts

The term *adaptive innovation* in this study refers to an innovation process that evolves in response to changing environmental, technological, and organisational conditions. It is not confined to a single design or implementation stage. It adapts to feedback from practice, shifting stakeholder needs, and emerging opportunities. In healthcare AI, adaptive innovation can be considered when a predictive algorithm for stroke risk is iteratively refined as new patient data and clinical guidelines become available (Teece et al., 1997; Tushman & Romanelli, 1985).

Strategic adaptation is conceptually distinct. It focuses on the organisation's capacity to adjust its structures, resources, and processes in alignment with long-term goals when external or internal contexts change. Strategic adaptation in AI integration may involve reconfiguring hospital governance to support AI oversight, reallocating budgets towards data infrastructure, or revising recruitment to attract AI-skilled staff (Chakravarthy, 1982). While adaptive innovation operates at the level of the service, strategic adaptation operates at the institutional and system levels to enable such innovations to succeed.

A *continuous approach* in this context describes an implementation pathway that is cyclical. AI technologies evolve rapidly, and healthcare systems must adjust according to it. One-time deployments risk misalignment with updated clinical practice. A continuous approach ensures that AI initiatives remain integrated with evolving evidence, regulatory requirements, and operational realities. For example, an AI tool in emergency departments can be periodically revalidated, retrained, and redeployed, maintaining accuracy and equity in patient care. This need for continuity arises from the interplay of rapid technological development, variable data quality, and shifting healthcare priorities, all of which can undermine static implementation strategies (Vial, 2019; Wessel et al., 2021).

2.2. Artificial intelligence in healthcare

John McCarthy in 1959 initially defined AI as the development of intelligent machinery using computer algorithms, a concept that has since evolved (Mccarthy, 1959). Today, AI refers to a system's ability to interpret external data, learn from it, and use this knowledge to achieve specific tasks through adaptable methods (Kaplan & Haenlein, 2019). These foundational efforts laid the groundwork for AI's integration into healthcare, initially in data analysis and decision support systems.

Since the 2000s, exponential advancements in computational power, algorithms, and data availability have significantly expanded AI's role in healthcare. Applications now include diagnostic imaging, EHR management, and robot-assisted surgery, along with predictive analytics, personalised medicine, and new therapeutic developments. Successful integration requires strategic alignment of AI initiatives with healthcare goals (Topol, 2019). Comprehensive assessments can help organisations identify high-impact areas for AI, ensuring that implementations drive both immediate and long-term objectives (Shortliffe & Sepúlveda, 2018). The synergy between human insights and AI's analytics is critical, especially in complex decision-making scenarios (Havlovska et al., 2020; Mirbabaie et al., 2021).

Collaboration among technology providers, healthcare institutions, and academia fosters the development of effective AI solutions. Examples include partnerships like the Mayo Clinic and Techcyte, aiming to revolutionise pathology through AI, improve treatment efficiencies, and expand access to global healthcare (Caine et al., 2022). Addressing ethical challenges is equally crucial. Transparent AI decision-making and regular audits for biases are necessary to build trust and ensure fairness, as emphasised by the World Health Organization (2021) and Obermeyer et al. (2019).

AI-focused organisations must also continuously adapt to technological advancements, regulatory changes, and evolving patient needs. The literature points to a gap in frameworks for AI adaptation in healthcare, highlighting the need for future research to develop methodologies that help healthcare systems effectively integrate AI and remain competitive in a dynamic environment.

2.3. Positioning within the existing literature on AI in healthcare

Recent research on AI adoption in healthcare has primarily focused on either technical efficacy (e.g., performance of diagnostic models or algorithms) or isolated use cases such as radiology, dermatology, and administrative automation (Hosny et al., 2018; Wei et al., 2024). While these studies have advanced algorithmic development and provided evidence of local improvements, they often lack engagement with the broader organisational and systemic contexts in which AI operates. For example, Yu et al. (2018) and Topol (2019) emphasised the clinical value of AI but did not address how such technologies can be embedded into institutional processes or scaled across healthcare systems. Similarly, reviews by Secinaro et al. (2021) and Mirbabaie et al. (2021) mapped AI applications across clinical domains but did not investigate the organisational readiness or transformation processes required for sustainable integration.

Furthermore, there is a limited number of studies that explicitly link AI implementation to established change management or strategic adaptation theories. Although some conceptual frameworks exist, for example, digital maturity models (Ochoa-Urrego & Peña-Reyes, 2021) or health innovation diffusion theories (Green et al., 2009), they rarely offer guidance on managing iterative organisational change, cross-functional coordination, or the continuous feedback loops required in real-world healthcare environments. This gap is particularly salient given the complexity of healthcare systems, which require coordinated change across technological, cultural, regulatory, and workforce dimensions.

Previous studies have often examined technology adoption in healthcare using established acceptance and diffusion frameworks such as the Technology Acceptance Model (TAM) (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and the Diffusion of Innovations theory (DOI) (Rogers, 2003). While these models provide valuable insights into individual and organisational adoption drivers, they primarily conceptualise adoption as a discrete event rather than as an iterative and adaptive process. In the context of AI in healthcare, this event-oriented framing can overlook the dynamic interactions between technology capabilities, organisational structures, and evolving system-level requirements. The AI-HSC framework extends beyond these adoption models by embedding change management structures, dynamic capability development, and system-level alignment into a continuous innovation cycle.

2.4. Integrating the theoretical framework

The AI-HSC framework combines Kotter's 8-Step Change Model, Dynamic Capabilities Theory, and Systems Theory to create a multi-level approach for guiding AI integration. Each theory was selected for its ability to address distinct but complementary challenges in healthcare innovation. Kotter's model provides a structured framework for managing organisational change. Its use is widespread in healthcare transformation studies due to its practical focus on leadership, urgency creation, communication, and cultural anchoring. While Kotter's 8-Step Change Model is traditionally applied to irregular and large-scale change initiatives (Kotter, 1996), its structured system of urgency creation, coalition building, and vision development can be adapted to support continuous innovation cycles. In this study, Kotter's model is not used as a one-off transformation plan, but as a governance framework integrated within an iterative process of sensing, seizing, and transforming. Each step is revisited at different points in the AI-HSC, with the pace and focus adjusted according to feedback from earlier iterations. For example, urgency creation is renewed when new AI capabilities or regulatory changes emerge; coalitions are reconfigured as pilot projects scale or shift focus. This cyclical application aligns with recent work on agile and adaptive change management in healthcare, where established models are applied in shorter, repeatable loops to sustain innovation momentum (Neumann & Purdy, 2023; Wessel et al., 2021).

We incorporate Dynamic Capabilities Theory, which conceptualises how organisations adapt over time by sensing opportunities, seizing resources, and transforming internal processes (Teece et al., 1997). This theoretical lens is especially relevant for AI, where rapid technological evolution demands organisational agility and reconfiguration. Systems Theory, as articulated by von Bertalanffy (1969), adds a crucial layer by highlighting the interconnected nature of healthcare institutions. Changes in clinical practice affect regulatory, administrative, and technological subsystems. This interdependence means that AI interventions cannot be viewed in isolation. Systems Theory ensures attention to feedback loops, unintended consequences, and the need for alignment across all levels of the organisation. Together, these three frameworks allow the AI-HSC to account for the structural, adaptive, and systemic dimensions of AI adoption. The model is designed to move beyond static implementation checklists and instead facilitate a dynamic, feedback-driven process of innovation. In this study we refer to this governance arrangement as a dynamic adaptation framework: a structure in which AI tools, associated workflows, and organisational arrangements are continuously adjusted on the basis of outcome data and stakeholder feedback, consistent with recent work on iterative digital transformation and adaptive change in healthcare settings (Neumann & Purdy, 2023; Vial, 2019; Wessel et al., 2021). Theoretical coherence and application are demonstrated through the mapping of each framework to empirical findings in the literature, organised by the model's four phases.

The relationship between Kotter's model, Dynamic Capabilities Theory, and Systems Theory within the AI-HSC is considered as a cyclical, reinforcing process feedback from pilot AI implementations helps as the operational initiation for this interaction. In practical terms, performance data and qualitative user feedback collected during early tests notify the sensing stage of Dynamic Capabilities, enabling the identification of emerging opportunities or risks in clinical and operational contexts. These insights activate seizing actions, such as reallocating resources, refining AI algorithms, or expanding interdisciplinary coalitions, which correspond to Kotter's empowerment and short-term win stages. The transforming phase addresses structural changes, including workflow restructure or regulatory adaptation, supporting Kotter's consolidation and institutionalisation steps. Systems Theory supports each stage by guaranteeing that feedback loops link the interdependent systems and subsystems. Therefore, technical adjustments in AI tools are coordinated by concurrent changes in training, governance, and patient engagement processes. This integration guarantees that each theoretical lens retains its individual role and contributes to a clear, operationally viable pathway for AI adoption.

Consider a triage AI for emergency computed tomography scans: (Pilot feedback) shows reduced time to read by 18%. (Dynamic Capabilities – sensing): leaders detect opportunity to expand to stroke pathways; (Kotter – urgency) is refreshed with comparative throughput data; (Systems lens) flags dependencies with Emergency Department staffing and Picture Archiving and Communication System integration. (Dynamic Capabilities – seizing): resources shift to integrate with order entry; (Kotter – coalition) adds Emergency Department nurse leads and IT security. (Dynamic Capabilities – transforming): workflows and access controls change; (Kotter – empower/wins): protocols updated, early wins reported. Feedback loops then prompt re-sensing (equity/false positives at night shifts), re-seizing (targeted retraining; Machine Learning Operations schedule), and re-anchoring (quality dashboards), showing the cyclical AI HSC in practice

3. Method

3.1. Theoretical model development

The development of the AI-HSC model is methodologically grounded in a systematic analysis of literature, utilising Kotter's 8-Step Change Model as a guiding framework. Our comprehensive literature review identified existing gaps and key challenges in AI adoption within healthcare settings, which were organised according to Kotter's steps to highlight critical areas such as the need for urgent action, coalition-building, and strategic vision in healthcare AI integration. Building upon this structured categorisation, we integrated key principles from adaptation theory (Chakravarthy, 1982; Tushman & Romanelli, 1985), specifically applying it to improve the model's capacity for addressing dynamic and complex healthcare environments. Each phase of AI adoption was aligned with corresponding steps in Kotter's model. The theoretical model underwent iterative refinement, aligning with empirical findings from recent AI integration studies and experts' opinion.

3.2. Kotter's 8-Step change model

Kotter's 8-Step Change Model serves as the framework for analysing adaptation of AI in the healthcare industry. The model's steps are as follows:

Establishing a sense of urgency: This step is about building momentum for change by making the need for action clear and immediate. It involves identifying critical risks or opportunities and communicating their importance to motivate stakeholders. Without urgency, the change effort risks stagnation.

Forming a powerful guiding coalition: This step focuses on forming a team of influential leaders to drive the change process. It emphasises collaboration and ensuring the team has the right mix of expertise, credibility, and authority. A strong coalition builds trust and alignment across the organisation.

Creating a vision: This step is about defining a clear vision that outlines the desired future state and providing a strategy to achieve it. The vision serves as a guiding principle, while the strategy breaks it into actionable steps. Together, they ensure the organisation remains focused during the transformation.

Communicating the vision: This step highlights the importance of sharing the vision broadly and effectively to ensure everyone understands and supports it. Consistent messaging through various channels helps address concerns and inspires alignment. Successful communication lays the groundwork for collaboration and action.

Empowering others to act on the vision: This step focuses on removing barriers and creating an environment where employees can contribute to the change effort. It involves addressing structural or cultural obstacles and providing resources and authority to act. Empowerment fosters innovation and accelerates the transformation process.

Planning for and creating short-term wins: This step is about achieving quick, visible successes that build confidence in the change initiative. Early wins demonstrate progress and provide tangible proof that the effort is worthwhile. Celebrating these milestones keeps stakeholders engaged and motivated.

Consolidating improvements and producing still more change: This step ensures that early successes are used as a foundation for broader change. It's about maintaining momentum by building on initial achievements and addressing deeper, systemic issues. Sustained progress prevents regression and drives lasting transformation.

Institutionalising new approaches: This step focuses on embedding new behaviours and practices into the organisational culture to ensure long-term success. It aligns systems, processes, and values with the change vision. Anchoring changes in culture makes them resilient to future challenges.

3.3. Data sources and search strategy

The data collection phase followed the principles of a systematic literature review (Paul & Criado, 2020), beginning with the identification of peer-reviewed studies related to the application of AI in healthcare. A comprehensive search was conducted across established academic databases, as illustrated in Figure 1.

Data were collected through a systematic search conducted in two databases: Scopus and Web of Science. The search strategy combined keywords related to artificial intelligence ("AI", "machine learning", "deep learning", "healthcare algorithms"), healthcare systems ("digital transformation", "clinical implementation", "hospital innovation").

The initial search yielded 4421 records from Scopus and 3237 from Web of Science. After automatic and manual deduplication ($n = 2444$), the records were filtered using the following inclusion and exclusion criteria:

Inclusion criteria:

- Peer-reviewed articles published between 2014–2024.
- English-language publications.
- Empirical or conceptual studies on AI adoption in healthcare systems.
- Studies referencing change frameworks or organisational integration models.

Exclusion criteria:

- Studies without substantial focus on AI implementation or adoption.
- Publications unrelated to healthcare delivery or organisational processes.
- Papers lacking theoretical grounding in change management, systems thinking, or strategic capabilities.
- Conference abstracts, editorial commentaries, or non-peer-reviewed literature.

After screening abstracts and titles ($n = 3787$), 2371 studies were excluded. Full-text assessments were conducted on 1416 papers, leading to the final inclusion of 33 studies that directly aligned with Kotter's 8-Step Model and demonstrated application of AI in healthcare. The final list of articles included in our research is presented in Appendix A.

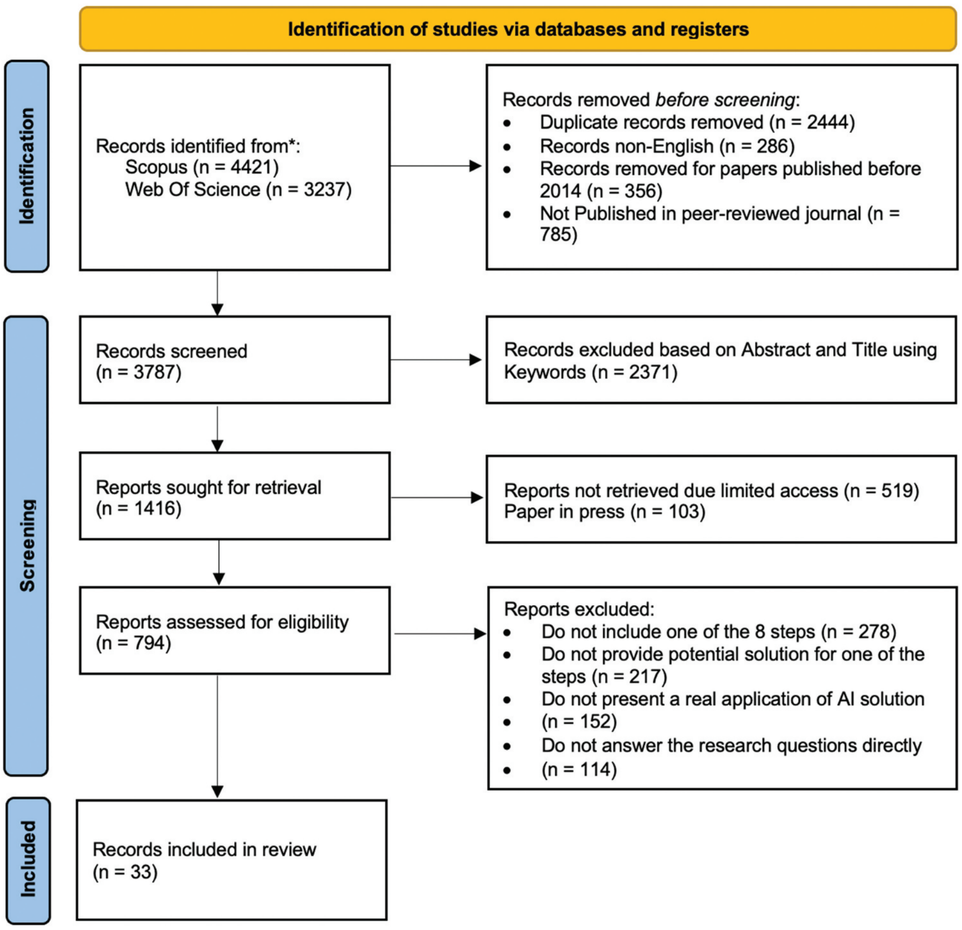

Figure 1. PRISMA flow diagram of the study.

3.4. Data analysis and verification

A qualitative thematic content analysis was used to interpret the selected studies. The analysis was structured around the core phases of Kotter's 8-Step Change Model. Each study was read and coded according to a deductive scheme informed by the model's steps: urgency creation, coalition building, vision formation, vision communication, empowerment, generation of short-term wins, consolidation of gains, and institutionalisation.

In addition, inductive codes were generated for emerging concepts related to ethical governance, regulatory adaptation, workforce readiness, and data integration. These were clustered and cross-referenced with the primary codes to examine how AI adoption intersects with systems theory (interdependencies, feedback loops) and dynamic capabilities (sensing, seizing, transforming).

The full coding process involved the following analytical steps:

- Open coding of all 33 included studies using NVivo software.
- Application of both deductive (model-driven) and inductive (emergent) codes.
- Code clustering into macro-themes mapped to AI-HSC phases.
- Triangulation of findings with theoretical constructs from Kotter's, Teece's, and Bertalanffy's frameworks.

3.5. Validation and expert review

To ensure clarity and practical relevance of the AI-HSC framework, a structured expert workshop was conducted involving professionals from the fields of healthcare management, clinical informatics, and AI system development. The workshop took place in a hybrid format, allowing both in-person and online participation to involve international contributors. Participants included twelve experts selected based on their experience with AI deployment in clinical settings, digital health strategy, or academic research on healthcare transformation. Four were senior executives from large hospital systems with decision-making authority over digital transformation initiatives. Three were clinical informaticians with direct experience in implementing AI-enabled clinical decision support tools. Two were data scientists employed in healthcare technology companies focusing on predictive analytics and medical imaging applications. Two were health policy specialists with backgrounds in regulatory compliance and ethical governance of digital health solutions. One was an academic researcher specialising in organisational change in healthcare. This composition ensured that perspectives from leadership, clinical operations, technical development, policy, and scholarly research were included. Participants were selected to reflect diversity in institutional type (public hospitals, private health systems, technology vendors, and academia) and geographical setting (Europe, North America, and Asia-Pacific).

The workshop followed a structured process that combined individual consultations with a moderated group discussion. Experts received the draft AI-HSC manuscript in advance, as well as clarity, feasibility, theoretical alignment, and the definition of phases comments. During the session, each participant provided feedback. The discussion was organised so that areas of consensus, differences in perspective, and practical recommendations were clearly captured. All workshop discussions were documented through detailed notes. The resulting material was analysed using a structured qualitative procedure that illustrated the approach applied to the literature. First, two authors independently coded the expert inputs using a deductive schema based on the four AI-HSC phases and Kotter's eight steps, complemented by inductive codes for emergent themes such as phase boundaries, governance responsibilities, and feedback mechanisms. Second, coding discrepancies were discussed until consensus was reached, and an audit trail was maintained to record how clusters of expert comments informed specific refinements of the framework.

The feedback was reviewed systematically to identify where adjustments to the model were required. Several participants emphasised the importance of distinguishing more clearly between the "evolution" phase, which centres on capability building through pilot projects and short-term wins, and the "revolution" phase, where AI becomes integrated across all organisational processes. Others suggested modifying the order of certain change steps. For example, placing consolidation activities earlier to better support repeated improvement cycles. In addition, participants recommended making the links between phases and feedback loops more explicit, ensuring that the framework could be applied iteratively.

These recommendations were incorporated into the final version of the AI-HSC. The resulting framework retained its theoretical foundations in Kotter's 8-Step Change Model, Dynamic Capabilities Theory, and Systems Theory, while reflecting insights drawn directly from practitioners with first-hand experience of AI adoption in healthcare. This process strengthened the model's operational relevance and ensured its adaptability to the realities of complex healthcare environments.

4. Findings

The findings are presented in an order that follows Kotter's 8-Step Change Model, but their interpretation within AI-HSC also based on Dynamic Capabilities and Systems Theory in combination. Evidence from the literature shows how each change stage is a part of a cycle in which feedback from AI implementations informs sensing – seizing – transforming activities. For example, early diagnostic improvements identified in pilot projects (short-term wins) generate new opportunities that are sensed and seized through resource reallocation or coalition expansion, while Systems Theory ensures these adjustments are coordinated across technical, clinical, and governance subsystems. This cyclical interaction is repeated throughout the phases, making the framework operational and adaptive in real healthcare environments.

The findings answer RQ1 by showing that AI adoption follows a cyclical pattern in real settings. Evidence across the reviewed studies shows repeated sensing, seizing, and transforming activities that align with Kotter's steps and cut across interdependent subsystems. This observation supports the move from linear implementation to a continuous approach supported by feedback and reconfiguration. The findings answer RQ2 by identifying the governance and capability choices (ethics oversight, data readiness, coalition design, pilot design, training) that allow this cycle to continue. Ethics oversight, data readiness, coalition design, pilot design, and training emerge as the conditions that mediate the path from vision to institutionalisation.

4.1. Establishing a sense of urgency

The rapid advancement and integration of AI in healthcare are essential, driven by the increasing demands to reduce costs, improve overall patient outcomes and diagnostic accuracy. The literature provides compelling evidence that highlights the urgent need for healthcare systems to adopt AI technologies (Dwivedi et al., 2021; Secinaro et al., 2021). Studies highlight AI's role in areas such as skin cancer detection. For instance, research has demonstrated that AI-enabled mobile health applications can significantly increase the accuracy and speed of diagnosing malignant and pre-malignant skin conditions, thus alleviating dermatologists' workload and enhancing early detection rates (Esteva et al., 2017; Wei et al., 2024).

AI's application in diagnostics is also emphasised in studies focusing on tissue sample analysis. Collaborations between AI developers and healthcare providers show that AI models can optimise diagnostic processes and clinical trials, improving the precision of disease diagnoses and therapeutic outcomes (Rajpurkar et al., 2018). The integration of AI in blood testing for conditions like stroke and atrial fibrillation has further been identified as a valuable innovation, reducing hospital costs and increasing diagnostic accuracy, as noted in research examining AI's impact on clinical workflows (Topol, 2019).

The urgency for deploying AI in medical imaging is also well-documented. Literature on AI's use in radiology describes how it improves diagnostic efficiency by quickly and accurately interpreting imaging data. Such advancements in medical diagnostics are crucial for maintaining high-quality patient care and ensuring timely treatment interventions (Haleem et al., 2022). These findings highlight the potential to significantly elevate service standards and patient safety (Jiang et al., 2017).

4.2. Forming a powerful guiding coalition

Literature emphasises the necessity of multidisciplinary coalitions for successful AI integration in healthcare. These coalitions typically include IT experts, healthcare professionals, and strategic leaders (Yu et al., 2018). The Coalition for Health AI (CHAI™) serves as a model, gathering a diverse group of stakeholders to promote AI applications' safety, equity, and transparency in healthcare. Similarly, the Artificial Intelligence Industry Innovation Coalition (AI3C) unites academia, healthcare, and tech industry leaders, such as the Brookings Institution and Cleveland Clinic, to address healthcare challenges through AI and support equity and workforce change (Haarhaus & Liening, 2020; Yu et al., 2018).

Studies also detail how interdisciplinary teams can effectively guide AI technology development. AiDoc exemplifies this with a leadership structure combining medical, research, and technological expertise to oversee AI algorithms and ensure their reliability in clinical practice. AliveCor's coalition approach, merging medical knowledge with tech innovation for cardiac monitoring, further illustrates how strategic leadership improves patient outcomes. These cases underline the essential role of diverse expertise in deploying AI solutions in healthcare (Rajkomar et al., 2019).

Research showcases the strategic formation of teams in biotech startups, which uses medical, engineering, and business backgrounds to accelerate drug design using advanced robotics. Another approach, involving specialists across departments to innovate cancer diagnostics, underscores the importance of compensating for organisational gaps with interdisciplinary collaboration. Collectively, these examples highlight the critical role of well-rounded coalitions in fostering innovation (Haarhaus & Liening, 2020; Rajkomar et al., 2019).

4.3. Creating a vision

Research emphasises the importance of developing a clear vision and strategy for AI integration in healthcare, as it provides direction and aligns organisational goals with technological advancements. A well-defined vision often prioritises increasing diagnostic accuracy, improving patient outcomes, and aiding healthcare professionals through AI applications (Kulkov, 2023). Effective visions are documented as essential in guiding developmental efforts and communicating objectives to key stakeholders, fostering support and adoption of AI technologies (Ciasullo et al., 2022).

Studies highlight the significance of a focused AI strategy. The organisational mission to decrease inefficiencies and expedite life-saving treatments reflects the essential role of strategic vision in AI-driven healthcare (Esteva et al., 2017). Similarly, a research-backed approach involves utilising computer vision and machine learning to offer personalised, unbiased digital diagnoses. This vision supports global improvements in patient care and exemplifies how strategic clarity in AI development can optimise medical outcomes (Yu et al., 2018). These findings underscore that a strong strategic vision in AI healthcare steers innovation and improves communication with external partners and internal teams (Ciasullo et al., 2022; Esteva et al., 2017).

4.4. Communicating the vision

Research highlights that clear and transparent communication increases stakeholder engagement and facilitates the adoption of AI solutions. Companies employ comprehensive strategies, including academic publications, updates from clinical trials, and proactive media engagement (Leone et al., 2021).

A company Qure.ai exemplifies this approach by using multiple channels to communicate the benefits of their AI-based imaging tools, like qXR and qER. Their strategy includes publishing in peer-reviewed journals, issuing white papers, and organising interactive live sessions with experts. This transparency helps build trust among healthcare professionals and validates their technology's impact on patient outcomes (Ngiam & Khor, 2019; Schiavone et al., 2021).

AI-driven tools are increasingly applied in healthcare cost containment, particularly in improving the accuracy and efficiency of billing and claims processing to reduce fraud. Companies specialising in this area often adopt open communication strategies to address potential concerns. For example, AI systems can analyse vast quantities of billing data to identify patterns that are indicative of fraudulent activities, which might be overlooked by human auditors. This approach also facilitates a deeper appreciation among stakeholders of how AI can improve operational transparency and accountability in healthcare, as noted by Reddy et al. (2020) in their study on AI applications in healthcare finance.

4.5. Empowering others to act on the vision

The literature identifies critical challenges in integrating AI into healthcare, such as resistance to change and technical limitations, which need strategic addressing. One significant barrier is the restricted access to proprietary data, which is essential for training AI models. Studies highlight that healthcare startups often face difficulties in acquiring comprehensive datasets due to privacy concerns and institutional restrictions (for example, Iacob and Simonelli (2020). Another significant barrier discussed in the literature is regulatory approval, which can be time-consuming and complex. The effectiveness of AI solutions is highly dependent on the availability of consistent, high-quality data, often impeded by fragmented data sources and strict regulations.

The studies demonstrate that addressing data access issues, navigating complex regulatory landscapes, and maintaining high data quality are essential strategies for successful AI integration in healthcare, setting a solid foundation for long-term success (Iacob & Simonelli, 2020; Ngiam & Khor, 2019).

4.6. Planning for and creating short-term wins

Securing early success is critical for effective AI integration in healthcare. Initial wins, like successful pilot projects that improve diagnostic processes or streamline administrative tasks, act as proof of AI's value. These achievements bolster stakeholder trust and support, laying the groundwork for broader adoption of AI technologies. Demonstrating that specific AI applications work effectively in localised settings (like a particular department or treatment type) paves the way for expanding these technologies across the healthcare organisation. A notable example is the use of AI in radiology, where deep learning models have been employed to improve the accuracy and speed of diagnostic imaging. A study by Rajpurkar et al. (2018) highlighted an AI model that outperformed radiologists in detecting pneumonia from chest X-rays, providing a strong early win that showcased the potential of AI to enhance diagnostic processes. Gaining regulatory approval is a crucial early win that can facilitate broader adoption. For example, the FDA's approval of AI-based diagnostic systems, such as IDx-DR for diabetic retinopathy, provided validation of AI's efficacy and safety, encouraging its adoption across other medical institutions (Abràmoff et al., 2018). The feedback gathered from initial deployments of AI technologies is invaluable. It provides direct insights into the functionality and impact of AI solutions in real healthcare environments. Following the achievement of short-term wins, it's essential to maintain momentum by engaging with all levels of the organisation. This includes regular updates to healthcare staff, stakeholders, and decision-makers about the benefits observed, challenges addressed, and the next steps planned.

4.7. Consolidating improvements and producing still more change

The literature emphasises that initial AI successes in healthcare are critical for encouraging the expansion of AI applications into broader medical domains. The integration of AI in healthcare has revolutionised several areas. A landmark application of AI in personalised medicine has been its use in oncology, where AI algorithms analyse genetic information and other biomarkers to recommend the most effective treatment strategies (Sebastian & Peter, 2022). For instance, companies like Tempus leverage AI to analyse both clinical and molecular data to provide personalised treatment plans that are showing promising results in improving patient outcomes (Bilgin et al., 2024). Following the early successes in oncology, AI technology has been extended to other medical fields, including medical imaging, healthcare research data management, and diagnostics in specialities like neurology and cardiology. For instance, in neurology, AI applications are being developed to detect patterns in data that could predict neurological events, such as seizures, well before they occur, thus enabling preventative measures (An et al., 2020). Similarly, in cardiology, AI tools are utilised to analyse echocardiograms to predict heart failure risks more accurately (Attia et al., 2019; Krittanawong et al., 2017).

4.8. Institutionalizing new approaches

As healthcare organisations transition towards AI integration, institutionalising these new approaches is essential. This process involves embedding AI within organisational structures and culture, making it an integral part of healthcare delivery (Caine et al., 2022; Hee Lee & Yoon, 2021). A prime example of this is the University Medical Center Groningen (UMCG) in the Netherlands, which has taken significant steps to embed AI in everyday healthcare interactions. This initiative marks UMCG as an early European adopter of patient-facing chatbots for written patient communication, showcasing an innovative approach to enhancing patient engagement and streamlining administrative processes. AI integration also extends to medical education. In addition to operational integration, educational initiatives are equally critical (Ngiam & Khor, 2019). For example, Yale School of Medicine has proactively incorporated AI and machine learning into its curriculum, emphasising the role of technology in areas such as telehealth, simulation, and pharmacology.

5. Developing an AI healthcare symbiosis cycle with Kotter's 8-Step change model

Traditional approaches to AI integration in healthcare often refer to AI as a supportive role, improving data analytics and operational efficiencies without changing healthcare practices. These models primarily augment the capabilities of healthcare professionals and improve diagnostic accuracy, yet they fall short in catalysing significant organisational change.

This paper introduces a novel framework which integrates with Kotter's 8-Step Change Model to facilitate a deeper, more systemic integration of AI into healthcare. Unlike traditional models, the AI-HSC does not treat AI as merely supplementary. Instead, it posits AI as an agent capable of reshaping healthcare processes and systems. This approach conceptualises AI integration as a dynamic, symbiotic process, where advancements in AI technology and healthcare practice continuously influence and improve each other.

The integration of Kotter's model provides a structured methodology for implementing this change, adapted to accommodate the iterative nature of AI evolution in healthcare settings. The AI-HSC model leverages interdisciplinary insights from fields such as information systems, healthcare informatics, and organisational change, drawing theoretical support from key studies that illustrate the profound impact of technology on organisational practices (Kruse & Beane, 2018; Meskó et al., 2017; Orlikowski & Iacono, 2001). The AI-HSC model uniquely aligns each phase with Kotter's steps, emphasising a continuous and adaptive integration process.

Initiation Phase: Establishing Urgency and Forming a Coalition. The process begins by recognising the urgent need to address inefficiencies in healthcare through AI solutions, aligning with Kotter's first step of creating urgency. This sense of urgency is critical to garnering the attention and commitment needed to drive substantial changes. It catalyses the formation of a robust coalition of healthcare executives, technology leaders, and key stakeholders – Kotter's second step. This powerful coalition is tasked with steering the strategic deployment of AI technologies

Integration Phase: Crafting and Communicating a Visionary Approach. As the initiative progresses, a visionary strategy is developed – Kotter's third step – outlining how AI will change patient care and improve operational efficiencies. This vision is then communicated throughout the organisation, ensuring commitment to the AI-driven change, resonating with Kotter's fourth step. The change gains further impulse as organisational barriers are taken apart and employees are empowered to innovate, which corresponds to Kotter's fifth step. This phase facilitates broader adoption of AI across diverse healthcare processes, emphasising the necessity of a supportive and adaptive organisational environment.

Evolution Phase: Empowering Others and Generating Short-Term Wins. The integration phase must empower others and produce short-term wins – Kotter's fifth and sixth steps – which are essential for maintaining impulse in the changing process. Early successes in AI applications provide tangible benefits that bolster stakeholder support and lay the foundation for further expansion of AI technologies. As these technologies mature, the Evolution phase begins, where AI's predictive capabilities and advanced analytics start reshaping clinical practices and treatment modalities.

Revolution Phase: Consolidating Gains Anchoring New Approaches in Organisational Culture and Institutionalising New Approaches. The final phase represents a significant leap where AI becomes a fundamental aspect of healthcare innovation – Kotter's seventh and eighth steps. In this stage, AI-driven insights lead to the emergence of new medical disciplines and change healthcare delivery systems. This impact necessitates a reevaluation of regulatory frameworks and ethical guidelines to accommodate the new technologies and approaches. The AI integration is fully secured into the organisation's culture and continues to evolve with the organisation's needs and external healthcare environment.

Sustaining cyclical evolution through AI-HSC and Kotter's Model by systematically applying Kotter's 8-Step Change Model within the AI-HSC framework, the methodology guides implementation of AI in healthcare and ensures a sustained, cyclical evolution. Each phase is designed to stimulate the next, facilitating continuous advancement.

5.1. Correspondence of AI-HSC with Kotter's 8-Step change model

Table 1 aligns the detailed phases of AI-HSC with Kotter's 8-Step Change Model – ranging from initial initiation to complete revolution – with the corresponding steps outlined by Kotter, involved key stakeholders, and expected outcomes of the project.

5.2. Implementation strategy and continuous improvement

To bridge the theoretical model with practical strategies for AI adoption, we developed strategic recommendations that are directly linked to the AI-HSC model. Figure 2 summarises these strategic recommendations as a phased roadmap that translates the AI-HSC into concrete implementation steps for healthcare organisations. Each recommendation draws from our theoretical analysis, highlighting how AI can be effectively deployed in healthcare organisations. By delineating clear phases – Initiation, Integration, Evolution, and Revolution – AI-HSC model directs organisations through the complexities of AI integration. Each phase is associated with specific steps from Kotter's model, providing a structured approach to change management.

Ethics and Compliance Framework for AI (Kotter's Step 1, AI-HSC Initiation Phase): Establishment of a comprehensive ethics and compliance framework for AI in healthcare guided by existing regulations and anticipated legal developments. This strategy is foundational during the Initiation phase where establishing a governance framework that complies with existing and future regulations is critical.

Table 1. Correspondence of AI-HSC with Kotter's 8-Step change model and Kotter's step.

Phase	Kotter's Steps	Key Stakeholders	Expected Outcomes
Initiation	Create a sense of urgency	Senior management, compliance officers, legal advisors	Awareness of the ethical and legal implications of AI, fostering a sense of urgency.
	Build a guiding coalition	Executives, department heads, AI specialists	A cross-functional team with authority and expertise to lead the change effort.
Integration	Develop a vision and strategy	AI strategists, healthcare professionals, IT leaders	A well-defined vision that aligns AI capabilities with clinical and operational goals.
	Communicate the vision	Organizational leaders, internal communication teams, staff	Stakeholder understanding, support, and alignment with the AI-driven goals.
Evolution	Empower broad-based action	Pilot program teams, IT support staff, operational managers	Identification and resolution of challenges in real-world AI applications.
	Generate short-term wins	Project managers, departmental leaders, healthcare providers	Demonstration of early success to build confidence and momentum for further change.
Revolution	Consolidate gains and produce more change	Training specialists, process improvement teams, AI developers	Improved capabilities and scalable solutions supported by ongoing feedback and adaptation.
	Anchor the changes in the culture	Regulatory bodies, monitoring teams, HR (for cultural alignment initiatives)	Sustainable AI integration into daily operations, supported by compliance and cultural shift.

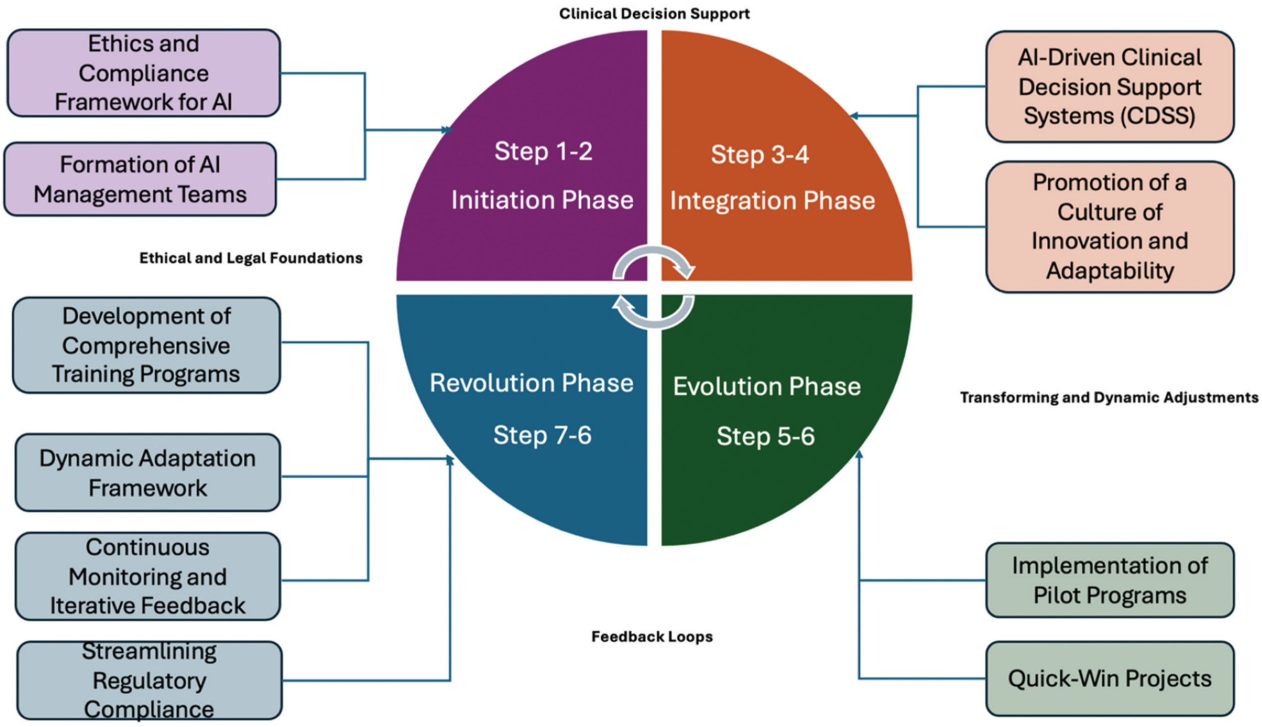

Figure 2. Schematic representation of the strategic recommendations for implementing AI in healthcare according to AI-HSC model.

Formation of AI Management Team (Kotter's Step 2, AI-HSC Initiation Phase): To sustain and expand AI initiatives, it is recommended to establish dedicated AI management teams that include IT specialists, data scientists, and clinical staff to ensure that AI systems remain functional, up-to-date, and relevant. Their tasks include system updates, problem resolution, and adaptation of AI tools to meet evolving healthcare demands. During the Evolution phase, dedicated AI management teams play a critical role in sustaining AI initiatives.

AI-Driven Clinical Decision Support Systems (Kotter's Steps 3, AI-HSC Integration Phase): Integration of AI-driven Clinical Decision Support Systems enables healthcare providers to analyse complex medical data for improved diagnosis and treatment planning. The vision should articulate how AI can augment clinical decision-making processes, and effective communication. Success metrics include improved diagnostic accuracy rates, reduced time to treatment, and increased clinician satisfaction.

Promotion of a Culture of Innovation and Adaptability (Kotter's Step 4, AI-HSC Integration Phase): Healthcare organisations are encouraged to foster a culture of innovation where continual learning, adaptability, and proactive involvement in AI initiatives are promoted. Essential in the Revolution phase, cultivating such a culture is pivotal for sustaining long-term AI integration and preparing the healthcare workforce for ongoing technological evolutions.

Implementation of Pilot Programs (Kotter's Step 5, AI-HSC Evolution Phase): The initiation of targeted pilot programs in pivotal areas such as diagnostic imaging and patient data management facilitate controlled experimentation. The planned selection of pilot areas is based on their potential for significant clinical impact, availability of comprehensive data for AI training, and readiness of technological infrastructure and staff. Success metrics for these pilots are predefined to include diagnostic accuracy, operational efficiency improvements, and user satisfaction levels. Following the pilot phase, successful AI applications are scaled based on systematic evaluations. This process includes improving technological infrastructure, expanding training programs to enclose broader range of healthcare staff.

Quick Wins Projects (Kotter's Step 6, AI-HSC Evolution Phase): Focusing on areas where AI can deliver immediate and tangible benefits helps build momentum for broader adoption. Implementing AI solutions in administrative tasks like scheduling, billing, or inventory management can provide quick wins that demonstrate the value of AI to the organisation. Achieving quick wins boosts confidence among stakeholders and reduces resistance. Success is measured by metrics such as reduced operational costs, improved workflow efficiency, and increased patient satisfaction.

Development of Comprehensive Training Programs (Kotter's Step 7, AI-HSC Revolution Phase):

As pilot programs validate the benefits of AI, the focus shifts to broader integration across healthcare operations. This phase involves developing training programs to prepare healthcare professionals for AI integration. Effective training is critical to reducing resistance and improving the adoption rate among clinicians. Success in this area is measured by improved user competence and acceptance. Simultaneously, building a guiding coalition of AI leaders – comprising healthcare executives, IT specialists, clinical leaders, and change agents – is essential for steering the AI integration efforts.

Operationalising the dynamic adaptation framework (Kotter's Steps 7, AI-HSC Revolution Phase): Development of a dynamic adaptation framework can actively modify AI algorithms based on ongoing feedback from clinical outcomes and patient satisfaction metrics. By removing barriers to change and facilitating quick adjustments, organisations can achieve additional wins such as enhanced patient outcomes and increased efficiency.

Continuous Monitoring and Iterative Feedback (Kotter's Step 8, AI-HSC Revolution Phase): The adoption of continuous monitoring and performance evaluations using data analytics is recommended to assess the impact of AI on healthcare metrics. This strategy is vital in both the Evolution and Revolution phases. Regular assessments and feedback are essential for iteratively refining AI applications, ensuring they adapt to changing healthcare needs.

Streamlining Regulatory Compliance Processes (Kotter's Steps 8, AI-HSC Revolution Phase): Implementing AI solutions to automate and improve regulatory compliance processes for tasks such as data auditing, reporting, and monitoring adherence to protocols, organisations can remove barriers associated with manual compliance efforts. This empowers staff by reducing the workload and leads to short-term wins through improved compliance rates, and reduced risk of penalties.

6. Discussion and theoretical contributions

The integration of AI into healthcare systems offers potential and introduces complex challenges that necessitate careful consideration. Prior studies have documented successful deployments of AI technologies to improve diagnostic precision in areas such as imaging and pathology (Jiang et al., 2017; Rajkomar et al., 2019; Topol, 2019). For instance, Rajkomar et al. (2019) demonstrated how deep learning algorithms could improve image interpretation in radiology and pathology, leading to more accurate diagnoses. Topol (2019) highlighted AI's impact on dermatology by enabling automated detection of skin conditions, thereby increasing diagnostic accuracy and efficiency. Despite these successes, AI integration presents challenges, including algorithmic biases and data privacy issues. Obermeyer et al. (2019) identified racial bias in health algorithms that result in disparities in care, raising ethical concerns about AI deployment. Additionally, the sensitive nature of medical records poses data privacy risks, such as unauthorised access and breaches that may compromise patient confidentiality (Vayena et al., 2018).

This study introduces the AI-HSC, a model designed to facilitate the strategic integration of AI technologies within healthcare organisations. By aligning the AI-HSC with Kotter's 8-Step Change Model (Kotter, 1996), Dynamic Capabilities Theory (Teece et al., 1997), and Systems Theory (Bertalanffy, 1969), the model provides a comprehensive approach to address the complex nature of AI adoption. Applying Kotter's 8-Step Change Model within the AI-HSC framework extends change management theory into the domain of AI integration in healthcare. The model adapts Kotter's steps to accommodate the rapid technological advancements and ethical considerations natural in AI technologies. The AI-HSC model operationalises Dynamic Capabilities Theory by providing strategies for healthcare organisations to adapt, integrate, and reconfigure internal and external competencies in response to technological changes. It highlights the importance of sensing opportunities and threats, seizing opportunities through strategic investments and collaborations, and changing organisational processes to accommodate new technologies (Teece et al., 1997). By applying Systems Theory, the AI-HSC model recognises healthcare organisations as complex, interrelated systems. The model addresses the need to optimise interactions between various organisational components during AI integration, confirming that changes in one area (e.g., technological infrastructure) are integrated with others (e.g., clinical workflows, regulatory compliance). The AI-HSC model recommends viewing AI integration as an iterative, cyclical process requiring ongoing adaptation and evolution, rather than as a linear, one-time event. The traditional linear models of technology adoption fail to capture the dynamic interplay between technological advancements and organisational change (Vial, 2019; Wessel et al., 2021). The AI-HSC model fills this gap. By mapping empirical insights to Kotter's steps and aligning them with dynamic capabilities and system-level interactions, the AI-HSC provides a structured yet flexible approach to long-term AI integration. Unlike traditional technology adoption models that prioritise initial uptake or user acceptance (Green et al., 2009; Ochoa-Urrego & Peña-Reyes, 2021), this framework supports a process of organisational transformation that explains over time and across functions (Neumann & Purdy, 2023). It operationalises adaptive change, anticipates systemic feedback, and positions AI not as a one-time intervention but as a continuously evolving driver of institutional development. In doing so, the AI-HSC offers a novel contribution to the ongoing discourse on healthcare digitalisation by addressing implementation as a process of strategic and systemic alignment, rather than isolated deployment.

Despite the potential benefits, several challenges may impede the successful implementation of the AI-HSC model. Resistance to change among healthcare professionals, data privacy concerns, and the need for significant investment in technological infrastructure are notable barriers. Additionally, the heterogeneity of healthcare systems and varying levels of technological maturity across organisations may affect the generalisability of the model. Developing comprehensive training programs and fostering a culture of innovation are crucial for overcoming resistance among healthcare professionals. Education can alleviate fears of job displacement by emphasising AI as a tool that augments rather than replaces human expertise (Kulkov et al., 2020; Meskó et al., 2017). Furthermore, addressing ethical and regulatory challenges through the establishment of robust compliance frameworks is essential for building trust and ensuring patient safety (Morley et al., 2020). Moreover, many of these issues resonate with those observed in other innovation domains. For instance, the introduction of EHRs faced resistance due to workflow disruptions, lack of interoperability, and professional scepticism. There barriers are also evident in AI deployment. Similarly, telemedicine initiatives have met regulatory ambiguity, data governance complexities, and disparities in digital readiness among providers and patients. What distinguishes AI, however, is the opacity of algorithmic decision-making, the dependency on large-scale, high-quality data, and the difficulty of ensuring explainability in clinical settings. These characteristics intensify the ethical and institutional concerns surrounding its implementation. By situating AI within the broader context of digital innovation in healthcare, it becomes clear that successful integration depends on technical performance and aligning with systemic conditions and organisational change processes. The AI-HSC model is designed with this cross-domain applicability in mind, offering a structured yet flexible approach to managing innovation in complex health systems.

7. Practical implications

AI-HSC offers a structured pathway for AI integration in healthcare organisations by linking organisational change steps with strategic capabilities and systems-level coordination.

In the Initiation phase, establishing urgency and building a guiding coalition require leadership engagement and a clear framing of institutional risk and opportunity. In small clinics, urgency can be communicated through direct patient outcome data or resource constraints, while large hospitals may require formal business case presentations and external benchmarking. In public systems, policy alignment and buy-in are critical, whereas in private institutions, executive sponsorship and investment logic often drive the case.

In the Integration phase, creating and communicating a vision demands suitable strategies. Clinics benefit from operationally specific visions, while larger hospitals require institution-wide strategic discussions. Public systems should align vision statements with national health priorities or digital health strategies, while private organisations may focus on competitive advantage or service differentiation. Communication strategies must be multichannel and role-specific, particularly in environments with layered hierarchies or unions.

In the Evolution phase, empowerment and short-term wins are crucial to gaining internal traction. For smaller organisations, this may involve AI deployment in administrative processes such as appointment scheduling or billing, which can offer quick and measurable returns. Large hospitals can pilot AI in high-impact clinical areas like radiology or oncology. Public institutions should demonstrate policy compliance and equity gains early, while private systems may prioritise ROI or patient satisfaction metrics. Empowerment also includes staff training, with smaller modular settings, on-the-job formats and larger ones investing in scalable e-learning platforms.

In the Revolution phase, consolidating gains and institutionalising change require ongoing adaptation. This includes establishing feedback loops, audit mechanisms, and ethics committees to oversee long-term AI performance and governance. For public systems, this phase may involve integration into national quality frameworks or digital infrastructure plans. Private organisations should focus on continuous optimisation, vendor partnerships, and competitive monitoring. Cultural embedding is important across contexts, and includes creating AI leadership roles, aligning HR incentives, and fostering data-driven decision-making as a norm.

8. Limitations and future research

This study is conceptual in nature and is based on a systematic literature review complemented by expert validation. While the proposed AI-HSC framework draws on well-established theories and is grounded in the analysis of 33 high-quality studies, it has not yet been empirically tested in real-world healthcare environments. As such, several limitations should be acknowledged.

First, the literature sample, while diverse and thematically rich, may be influenced by publication bias and language restrictions. The review was limited to English-language, peer-reviewed articles published since 2014, which may exclude relevant grey literature or region-specific insights. Second, although the expert workshop provided valuable practical validation, it does not substitute for full-scale empirical testing across different healthcare settings. Third, the integration of Kotter's model, Dynamic Capabilities Theory, and Systems Theory is theoretically grounded but remains interpretive. The operational dynamics between these frameworks, particularly their interaction over time, require further empirical exploration.

Future research should empirically validate the AI-HSC model using mixed-method or longitudinal case study designs. One approach could involve implementing the model across a sample of healthcare organisations varying by type (e.g., small clinics, tertiary hospitals), ownership (public vs. private), and national health system structure (centralised vs. decentralised). Data collection could include process tracing, ethnographic observations, implementation metrics, and semi-structured interviews with clinical and administrative stakeholders. Comparative analysis would allow researchers to assess which components of the framework are context-sensitive and which exhibit generalisable utility. Particular attention should be given to how institutional maturity, regulatory environments, and leadership models affect the success of each phase of the AI-HSC. These empirical efforts will help refine the model, enhance its applicability, and support its integration into policy and practice.

9. Conclusion

This study introduces the AI-HSC, a theoretically grounded framework designed to guide the sustained and systemic adoption of AI in healthcare organisations. By integrating Kotter's 8-Step Change Model, Dynamic Capabilities Theory, and Systems Theory, the framework addresses both the structural and adaptive dimensions of AI implementation. It moves beyond narrow, application-specific models by positioning AI as a driver of iterative institutional transformation. The AI-HSC contributes theoretically by aligning strategic adaptation and systems-level interdependencies with a structured change management process. It offers healthcare leaders and policymakers a practical roadmap for initiating, scaling, and institutionalising AI across clinical and administrative domains. The framework's phased structure allows for context-sensitive application and supports feedback-driven evolution, making it suitable for complex, continuously evolving health systems.

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Data availability statement

Data is available upon reasonable request with the authors.

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