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Artificial Intelligence in UK healthcare: A Systematic Literature Review

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Abstract: Artificial intelligence (AI) is reshaping healthcare in the UK, especially in areas like diagnostics and healthcare management. This systematic literature review examines 22 peer-reviewed studies to assess current AI applications in UK healthcare and the extent of their alignment with human-centred design, focusing on stakeholder engagement using the Maximum Feasible Participation model. Applying both bibliometric and thematic analyses while adhering to PRISMA guidelines, the study categorizes AI across five key healthcare domains. Findings show a strong presence of AI in diagnostics and a preference for virtual health solutions. However, stakeholder engagement remains limited in the design and development process and there is a lack of real-world validation and public involvement. Incorporating insights from NHS policy documents and grey literature, the study highlights a gap between technological innovation and practical implementation. The study contributes by positioning stakeholder participation as a key mechanism linking AI design to adoption outcomes.

Keywords: AI; healthcare; diagnostics; innovation management; systematic literature review; human-centred AI.

1 Problem: Innovation Management Challenge

Artificial intelligence (AI) has become transformative across various sectors, including public-facing fields such as education (Fu et al., 2024) and healthcare (Bardhan et al., 2025; Shah and Chircu, 2018). These sectors share a clear trend: AI applications are expanding at an unprecedented rate, driven by advancements in machine learning (ML), automation, and big data analytics. In healthcare, AI already plays a vital role, enhancing diverse processes from medical imaging and diagnostics to real-time patient tracking and monitoring. AI-powered systems provide real-time insights into health conditions, assisting healthcare professionals in decision-making, treatment planning, and operational management (Zahlan et al., 2023). AI even aids complex surgeries, improving precision and efficiency (Zhou et al., 2020).

Despite such successes, AI adoption in healthcare faces unique challenges concerning stricter ethical aspects, regulation, and operational requirements (Bajwa et al., 2021). Issues such as patient safety, data protection policies, algorithmic transparency, and human clinical oversight require careful attention (Schneiderman, 2022). Additionally, research suggests that, while AI can outperform human healthcare professionals in specific tasks, patients still prefer to receive care from human providers (Gille et al., 2020). This underscores the importance of human-centred AI design to ensure AI tools remain aligned with real-world needs and, thus, enhance rather than replace human decision-making and interaction (Sit et al., 2020).

Against this backdrop, public healthcare systems face mounting pressure to improve service quality, efficiency, and accessibility under constrained resources and increasing demand. In the United Kingdom, these challenges are particularly visible within the National Health Service (NHS), which continues to struggle with long waiting times, workforce shortages, and rising care complexity (Anandaciva, 2023). These pressures are compounded by demographic changes, including an ageing population and rising prevalence of chronic disease, which further strain healthcare delivery systems. According to recent figures, 7.7 million patients are waiting for routine hospital treatment with 390,000 waiting more than a year (Nuffield Trust, 2023). These pressures expose systemic vulnerabilities requiring solutions beyond traditional policy changes, such as international staff-recruitment efforts and infrastructure investments (Freedman and Wolf, 2023).

In response, artificial intelligence (AI) is widely promoted as a transformative innovation capable of supporting diagnostics, clinical decision-making, and operational efficiency (NHS England, 2025). The UK is among the top three countries (alongside the US and China) investing in AI in healthcare, positioning itself at the forefront of integrating AI technologies to improve patient outcomes and operational efficiency. However, despite substantial investment and policy attention, the large-scale and sustainable adoption of AI in UK healthcare remains limited.

Similarly, while AI systems demonstrate strong technical capabilities, their translation into routine clinical practice remains uneven. This reflects a broader implementation gap between innovation and adoption (Greenhalgh et al., 2017). Many AI solutions remain confined to pilot projects or experimental settings, with limited evidence of integration into everyday workflows.

From a public sector innovation management perspective, the central problem is not technical feasibility but implementation and governance (Greenhalgh et al., 2017; Vial, 2019). AI systems intervene directly in sensitive domains such as clinical judgment, patient data, and care prioritization. This creates heightened concerns around trust, accountability, transparency, and ethical responsibility (Floridi et al., 2018; WHO, 2021). Innovation managers in public healthcare organizations must therefore balance technological opportunity with legitimacy, regulatory compliance, and stakeholder acceptance.

This paper addresses the innovation management problem of how AI is currently implemented in UK healthcare and whether these implementations align with human-centred and responsible innovation principles. Specifically, it focuses on the gap between rapid AI development and the integration of participatory, ethical, and governance-oriented practices that are essential for sustainable innovation in public-sector healthcare systems.

2 Current Understanding

Prior research demonstrates that AI technologies (particularly machine learning and deep learning) can support healthcare diagnostics, predictive medicine, and clinical decision support (Bardhan et al., 2025). Studies report performance improvements in areas such as medical imaging, risk prediction, and pattern recognition, often achieving results comparable to or exceeding human clinicians in controlled settings (Topol, 2019). However, popular presentations in media and science fiction often lead to misconceptions about AI's real-world capabilities (Strengler et al., 2023), and the field remains broad and evolving with no universally accepted definition (Jimma, 2023).

To provide conceptual clarity, the NHS Confederation (2024) defines AI as "the capability of a computer system to mimic human cognitive functions such as learning, problem-solving, interpreting visual information, understanding, and responding to spoken or written language [using] math, logic and patterns learned from data to simulate human reasoning and make decisions and recommendations." However, such definitional ambiguity continues to hinder AI adoption, as medical professionals and policy makers struggle to assess its potential and limitations (Collins et al., 2021).

More specifically AI is closely linked to ML, in which models learn from data for predictions or pattern-identification. ML is categorized (Morales & Escalante, 2022) as supervised (diagnosing from labelled medical images), unsupervised (clustering patient symptoms), and reinforcement learning (adaptive systems such as robot-assisted surgeries). Effective training requires large, diverse datasets, but healthcare data issues include overfitting, bias, and scarcity (Norori et al., 2021). These highlight the need for continuous validation and monitoring to ensure fairness and effectiveness across diverse patient groups (Carey et al., 2024).

Advanced techniques such as Deep Learning (DL) further expand AI's capabilities. DL relies on neural networks that process data in multiple layers, allowing complex pattern identification (LeCun et al., 2015). Computer vision, Natural Language Processing, and robotic process automation also offer advancements in diagnostics and personalized care. Generative AI and large language models introduce new possibilities in administrative and assistive roles but are not yet reliable for critical medical tasks due to potential misinformation (Floridi, 2023). Artificial general intelligence, which aims for human-level reasoning, remains a distant goal and underscores the narrow scope of AI (Fjelland, 2020).

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The diverse fields of AI in healthcare follow two branches: virtual and physical (Li et al., 2020). The virtual branch comprises computational tools that improve diagnostic accuracy, operational efficiency, and patient-facing applications with minimal physical hardware. The physical branch includes AI-assisted robots in clinical medical, auxiliary rehabilitation, hospital service, and medical teaching categories. For instance, surgical robots, introduced in 1985, have revolutionized minimally invasive procedures while enabling surgeons to work with enhanced precision (Datta et al., 2021).

Importantly, healthcare differs from private-sector contexts due to its ethical obligations, professional autonomy, and reliance on public trust. Many challenges predominantly stem from a predominant focus on technical optimization (such as performance accuracy and computational efficiency) without fully accounting for human values and ethical concerns central to healthcare environments.

Technology adoption research, particular the Technology Acceptance Model (TAM), highlights perceived usefulness and ease of use as key drivers of adoption (Davis, 1989). However, in healthcare contexts, additional factors such as trust, explainability, and accountability is critical. AI ethics literature further identifies risks related to algorithmic bias, opaque decision-making, and data privacy (Morley et al., 2020) all of which can undermine acceptance among clinicians and patients. Many AI models function as “black boxes,” making it difficult to interpret the underlying decision-making process, which is critical in medical settings requiring accountability (Lipton, 2018). Consequently, global regulatory frameworks therefore must adapt sector-specific guidelines to safeguard the responsible implementation of AI, particularly in healthcare.

Human-centred and responsible AI frameworks have emerged to address these concerns. These approaches emphasize stakeholder participation, transparency, and alignment with societal values (Floridi et al., 2018; (Taylor et al., 2024b). The UK adopted a sector-focused and principle-based approach to regulate AI in healthcare, highlighting the importance of evaluating whether AI implementations genuinely embody human-centred principles (Department for Science, Innovation & Technology, 2023). In the public sector, participatory models such as Maximum Feasible Participation (MFP) stress the importance of involving affected stakeholders in innovation processes (Taylor et al., 2024a).

In addition, AI adoption in healthcare can be understood within broader innovation management perspectives, including innovation eco-systems and public-sector digital transformation (Adner, 2017; Vial, 2019). These perspectives emphasise the interdependence of actors, such as policymakers, healthcare organisations, technology developers, and patients, in shaping innovation outcomes (Jacobides et al., 2018). Collectively, these approaches highlight the importance of governance structures in coordinating these actors and ensuring successful implementation. As such, AI implementation should be understood not merely as a technical challenge, but as a multi-actor, socio-technical innovation process.

While these concepts are well established conceptually, empirical studies systematically assessing the human-centeredness of AI implementations in UK healthcare remain limited. As a result, public-sector innovation managers lack evidence-based guidance on how responsibly AI is currently being deployed in practice.

Conceptual Perspective: Stakeholder Participation and AI Adoption

Stakeholder participation plays a critical role in shaping AI adoption outcomes in healthcare. Building on the Maximum Feasible Participation (MFP) model, stakeholder involvement can be understood as influencing adoption through several key mechanisms.

First, participation supports trust formation by increasing transparency and legitimacy among clinicians and patients. Trust is a central factor in healthcare, where clinicians and patients must rely on AI-supported decisions in high-stakes contexts (Gille et al., 2020; Asan et al., 2020).

Second, participation improves system alignment by ensuring AI tools reflect real-world clinical workflows and user needs. This enhances perceived usefulness, a key determination of adoption in the Technology Acceptance (TAM) Model (Davis, 1989). Systems that do not align with clinical practices are unlikely to be adopted, regardless of their technical performance.

Third, participation enhances ethical robustness by enabling early identification of potential risks, biases, and unintended consequences in the development process (Stilgoe et al., 2013). This is particularly important in healthcare, where ethical considerations are central to decision-making processes.

Collectively, these mechanisms influence key adoption outcomes, including clinician acceptance, integration into healthcare workflows, and sustained organisation use. This perspective positions stakeholder participation not only as a normative principle, but also a practical driver of successful innovation implementation in healthcare systems.

3 Research Question(s)

To address these gaps, the study is guided by the following research questions:

RQ1: What AI techniques and application domains are currently employed in healthcare in the United Kingdom?

RQ2: To what extent do current AI applications in UK healthcare adhere to human-centred and responsible innovation principles, particularly regarding stakeholder involvement, transparency, and ethics?

These questions explicitly link technological innovation with governance and participation, aligning with the focus on public sector innovation and responsible digital transformation.

4 Research Design

The study adopts a systematic literature review (SLR) methodology following PRISMA guidelines (Page et al., 2021). A hybrid approach combines bibliometric analysis with qualitative thematic analysis to capture both publication trends and substantive innovation management insights (Paul & Criado, 2020; Braun & Clarke, 2016).

Peer-reviewed journal articles published between 2015 and 2024 were identified through structured database searches using keywords related to artificial intelligence, healthcare, and the United Kingdom. Inclusion criteria restricted the sample to English-language journal articles focusing explicitly on AI applications in UK healthcare.

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Conference papers, book chapters, and grey literature were excluded. After screening, duplicate removal, and eligibility assessment, 22 peer-reviewed articles were retained for analysis (see Figure 1). CADIMA v2.2.4.2's duplicate identification features were used for screening (Kohl et al., 2018).

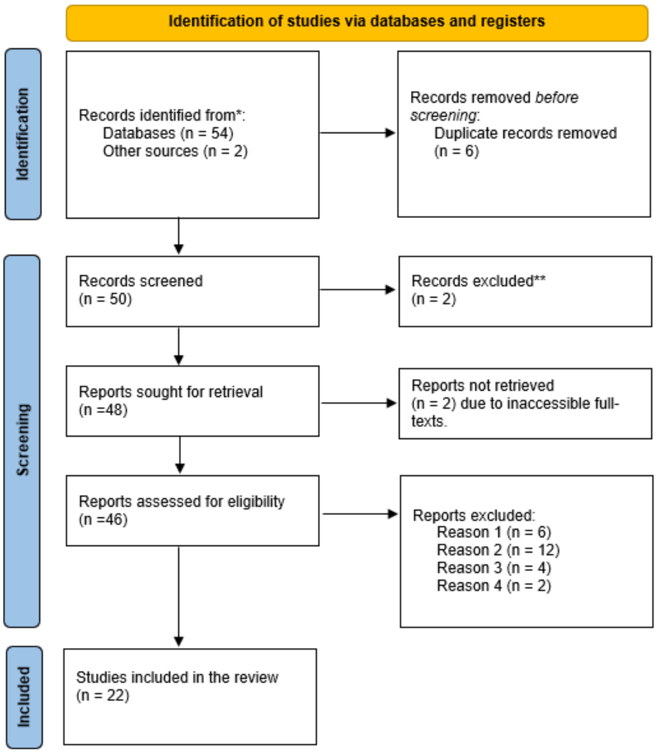

Figure 1 PRISMA

The review categorizes AI technologies into five key roles of AI in healthcare defined by Secinaro et al. (2021; health services management, predictive medicine, clinical decision making, patient data, and diagnostics) and systematically assesses stakeholder involvement in AI development using the MFP model (Taylor, O'Dell, et al., 2024).

Data were extracted from each article (bibliometric details, AI type), and findings were mapped to five key healthcare domains and clinical areas. The MFP model was used to evaluate the extent of stakeholder engagement. Finally, thematic analysis iwas conducted to identify emerging patterns related to AI adoption, stakeholder involvement, and ethical considerations. This combination of quantitative (bibliometric) and qualitative (thematic) approaches provides a rigorous and multi-faceted understanding of AI in the UK healthcare sector.

The analysis further integrates quantitative trend analysis with qualitative coding, to provide a comprehensive overview of AI innovation practices in UK healthcare. To enhance contextual relevance, insights from NHS policy documents and grey literature were considered during the interpretation phase (NHS Confederation, 2024). While not included in the formal dataset, these sources provide additional contextual insight into real-world AI implementation within the NHS.

5 Findings and Interpretation

The review included 22 peer-reviewed articles published between 2015 and 2024. Bibliometric analysis revealed a sharp increase in AI-related healthcare research in the UK, particularly since 2021. AI applications were first categorized either as virtual or physical. Most articles (18) focused on virtual AI applications; four addressed AI applications with physical components, such as wearables for healthcare monitoring at home. Most identified AI applications are software-based, reflecting a preference for virtual solutions that integrate into existing digital infrastructures.

AI applications were subsequently mapped across the five key healthcare domains. Most AI applications (8) aimed to support patient diagnostics. Further analysis involved mapping these AI healthcare domains across general clinical areas in healthcare (see Figure 2). The findings indicate that diagnostics, especially medical imaging and radiology, dominate the application landscape, followed by predictive medicine and clinical decision support.

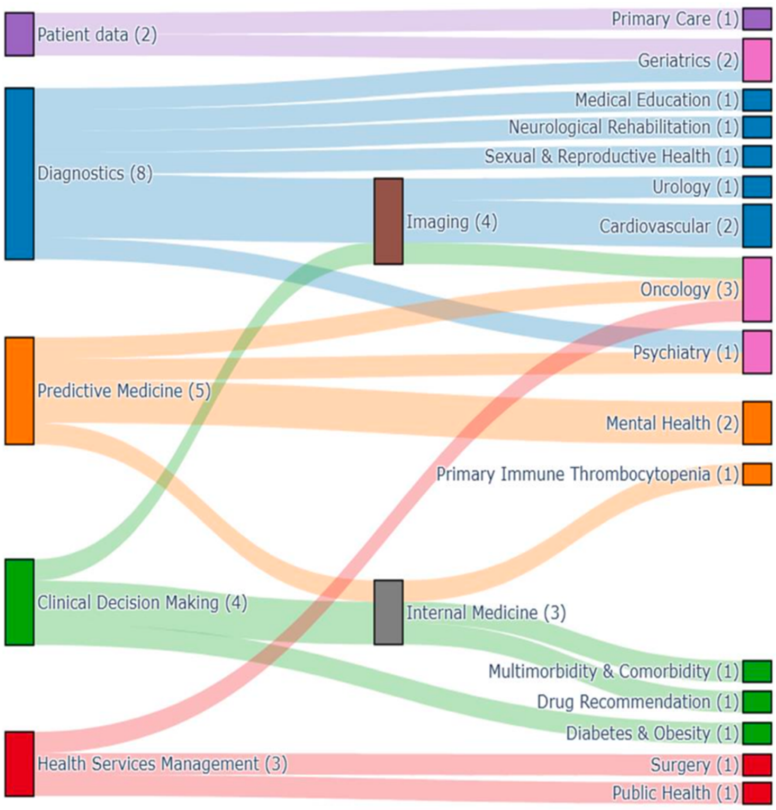

Figure 2 Overview of AI healthcare applications across healthcare domains.

The main AI applications identified focused on diagnosing, predicting, and managing health conditions, emphasizing diagnostic imaging and clinical decision support. The most prominent clinical areas were medical imaging, internal medicine, and mental health. Studies also focused on AI solutions for stroke rehabilitation (Standen et al., 2023), sexual and reproductive health (Nadarzynski et al., 2021), and frailty care (Taylor W. et al., 2024).

Building on these findings, a deeper thematic analysis explored AI application across the key healthcare domains and identified critical challenges affecting AI development and adoption. In the first domain, **diagnostics**, AI-enhanced tools are widely used to identify disease patterns from imaging or laboratory results, such as ML algorithms identifying cancerous lesions or DL reconstruction techniques for ultra-low-dose computed tomography (CT) scans in urology (Rauf et al., 2023). The second domain is **predictive medicine**, with several articles highlighting ML models to predict future illness onset or disease progression, such as using plasma metabolic profiles to forecast dementia (Qiang et al., 2024) or leveraging patient medical data to anticipate a mental health crisis (Guerreiro et al., 2024). In the third domain, **clinical decision-making**, AI-based systems support medical professionals in making complex decisions, including a drug-recommendation tool for mental health (Lee et al., 2024) and real-time staging of lymphoma (Frood et al., 2024). The fourth domain is **health services management** with AI applications used for triaging patients, resource allocation, and community-based monitoring, such as using a smartphone to monitor wound healing post-surgery (McLean et al., 2023). Finally, in the **patient data** domain, AI applications ensure data security and privacy, for instance, through Generative Adversarial Networks for synthetic patient data generation (Yoon et al., 2020) and You-Only-Look-Once-based models for blurring sensitive information in wearable camera footage (Moore et al., 2024).

Importantly, the results spotlight the need for human-centred approaches. Most AI tools were developed collaboratively by AI/ML engineers and healthcare professionals; only 2 of the 22 studies explicitly integrated healthcare consumers, patients, or the public in the process. This indicates minimal adherence to human-centred models like the MFP framework. While the majority of studies clearly outlined the benefits for healthcare consumers, actual healthcare consumer or patient involvement was lacking. This gap between stated patient benefits and actual stakeholder involvement suggests a significant disconnect between responsible AI principles and current implementation practices.

Four main findings emerged from the review:

1. **AI's role in tackling emerging healthcare challenges:** AI tools are used for a wide range of health conditions, many aligning with leading causes of death in the UK. Focus is on chronic illnesses, mental health, and rare diseases, illustrating AI's flexibility for disease-specific needs.
2. **AI dominance in diagnostics:** Most UK AI research explores AI-driven diagnostics, particularly in medical imaging with radiology as a primary testing ground; ML models help identify and characterize abnormalities in CT, MRI, and other imaging modalities. Concerns remain regarding degradation of clinical skills, overreliance on AI findings, and the need for human oversight.
3. **Preference for virtual AI health solutions:** This preference is driven by perceived ease of integration into existing digital workflows. Wearables, telemedicine, and chatbots exemplify such software-based AI; physical AI in the form of assistive robots is less prevalent due to cost, infrastructure, and a lack of policy frameworks within the NHS.

4. **Lack of stakeholder engagement in designing human-centered AI applications:** Challenges remain such as distrust by healthcare professionals, concerns over bias, and limited opportunities for patient participation in development. Only two reviewed studies (SysteMatic for multiple long-term conditions [Mair et al., 2024] and a sexual and reproductive health chatbot [Nadarzynski et al., 2021]) explicitly integrated patient co-creation, highlighting the gap between ambitions for stakeholder involvement and real-world implementation.

These findings suggest that, despite rapid advances in AI capabilities, the gap between technical innovation and human-centred principles persists. Attaining sustainable AI integration in healthcare means aligning with fairness, transparency, accountability, and participatory design frameworks.

At the system level, comparatively few AI applications target health services management or patient data governance, despite their relevance for public-sector efficiency and trust. While most studies frame AI as beneficial for clinicians and patients, explicit stakeholder participation in system design is rare.

Applying the MFP model reveals limited adherence to human-centred innovation principles. AI development is largely driven by technical and clinical experts, with minimal involvement of patients or the public. This lack of participation correlates with persistent concerns about transparency, explainability, and ethical accountability.

Overall, the findings indicate a disconnect between technological innovation and responsible innovation management in UK healthcare. A further disconnection is evident between NHS AI Labs, scientific publications, and real-world validation, limiting transparency and slowing broader clinical integration. Insights from NHS policy reports suggest that many AI initiatives remain at pilot stages, with limited large-scale implementation (NHS Confederation, 2024). Barriers such as data fragmentation, workforce readiness and governance complexity further constrain adoption.

These observations reinforce the gap identified between technological innovation and real-world application. In many cases, buyers and end-users lack access to robust validation or large-scale clinical trial data in publicly available literature, complicating efforts to assess real-world performance. The results corroborate previous findings that, although AI holds significant promise for addressing persistent needs in the UK healthcare system, considerable challenges remain regarding stakeholder engagement, data protection, and bridging the gap between research, regulations, and practice.

6 Contribution to the Innovation Management Community

This study contributes to innovation management research in three ways. First, it provides a systematic, public-sector–specific overview of AI innovation in UK healthcare, linking technological diffusion with governance and implementation challenges. It extends existing AI and healthcare literature by situating technological adoption within institutional and policy context of the NHS.

Second, it empirically applies human-centred and participatory frameworks to assess AI adoption, extending responsible innovation theory with sector-specific evidence on how stakeholder participation influences adoption outcomes in complex public-sector environments.

Third, the study advances public sector innovation theory by demonstrating that sustainable AI adoption depends not only on performance gains but on alignment with ethical principles, stakeholder engagement, and public trust. These findings strengthen the view of innovation as a socio-technical process requiring managerial capabilities beyond technology deployment. The study also highlights the role of stakeholder participation as a key mechanism linking innovation design to adoption outcomes in public-sector healthcare. These contributions are particularly relevant for innovation managers seeking to operationalise human-centred AI within complex and resource-constrained healthcare systems.

The study highlights stakeholder participation as a critical mechanism linking innovation design to adoption outcomes in public-sector healthcare, offering both theoretical and practical insights for managing AI-driven transformation.

7 Practical Implications

Among the strongest outcomes is the emphasis on bridging the gap between innovation and real-world application. Although AI is widely researched in the healthcare sector, it is not always extensively tested or validated in clinical settings (Muehlematter et al., 2021). Greater transparency from NHS AI Labs and large-scale trials are vital to ensure that AI applications meet standards of patient safety, equity, and practical utility.

Human-centred AI design emerges as the most urgent challenge and the greatest opportunity. While the UK’s principle-based regulatory approach promotes fairness, accountability, and transparency, these must be operationalized through co-design processes and inclusive stakeholder engagement (Thieme et al., 2023). Healthcare institutions and developers should involve public forums, patient-advocacy groups, and ethics boards early in development to ensure AI addresses genuine healthcare needs and mitigate potential biases.

For public-sector innovation managers and healthcare leaders, the findings highlight the importance of embedding governance and participation mechanisms into AI initiatives. AI projects should include structured stakeholder engagement processes involving clinicians, patients, and public representatives from early design stages. Establishing clear governance frameworks can support accountability, transparency, and alignment with organisational goals.

Policymakers and regulators can use these insights to refine AI guidelines and evaluation frameworks that prioritize human-centred criteria alongside technical performance. Technology developers gain guidance on designing AI solutions that better align with public-sector values and adoption requirements. In practice, organizations that manage AI as a responsible, human-centred innovation are more likely to build trust, reduce resistance, and achieve sustainable transformation outcomes in healthcare.

More broadly, organisations that manage AI as a responsible, human-centred innovation are more likely to build trust, reduce resistance, and achieve sustainable transformation outcomes in healthcare. Establishing clear pathways from pilot projects to large scale implementation can further support the successful integration of AI in healthcare settings. These implications are particularly relevant in resource-constrained healthcare systems, where effective implementation depends on aligning technological innovation with institutional capacity and stakeholder expectations.

8 Limitations and Future Research

This study has several limitations. First, the analysis is based on a relatively small sample of 22 peer-reviewed articles, which may limit the generalisability of the findings. Second, the study relies on secondary data and does not include primary empirical evidence from healthcare practitioners or policymakers. Third, although grey literature and policy insights were considered, these were not systematically analysed, which may introduce bias. Finally, the rapidly evolving nature of AI in healthcare means that findings represent a snapshot in time. Policy gaps and stakeholder scepticism can be addressed through continuous engagement, demonstration of AI benefits (Höpfl et al., 2023), and robust education programs for healthcare professional's expertise to support effective utilization of AI outputs (Sit et al., 2020). Overcoming these barriers requires close collaboration among regulators, NHS managers, AI developers, healthcare workers, and patients. AI offers promising prospects for enhancing diagnostics, predictive medicine, and clinical decision-making within the UK healthcare system. However, realizing these potential demands stronger stakeholder participation, transparent and systemic AI validation, and continuous ethical oversight. Future research should focus on larger clinical trials, comparability of AI performance across diverse populations, and formal frameworks that ensure stakeholder participation and continuous monitoring of ethical and clinical impacts. Additionally, future research should also incorporate primary data, such as interviews with clinicians, policymakers, and AI developers, to better capture real-world implementation dynamics. Expanding the dataset to include systematic analysis of grey literature would further enhance understanding of AI adoption in practice.

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