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Stakeholder Perceptions of Challenges and Benefits of AI in Diagnostic Imaging: A Systematic Thematic Exploration within the NHS

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ABSTRACT

This study critically investigates NHS stakeholder perceptions of artificial intelligence (AI) adoption within diagnostic imaging, exposing the socio-technical, ethical, and institutional tensions that underpin implementation challenges. Despite sustained policy investment, much of the extant literature remains techno-centric—overlooking the epistemic concerns, professional disempowerment, and legitimacy anxieties of frontline radiographers, radiologists, patients, and healthcare leaders. To address this gap, the study adopts a theory-informed secondary qualitative synthesis, integrating the Technology Acceptance Model (TAM) and Stakeholder Theory to interrogate how acceptance, trust, and governance perceptions shape AI readiness. Thirteen UK-based empirical studies (2020–2025) were selected through a PRISMA-guided protocol and analysed using Braun and Clarke's six-phase reflexive thematic analysis. Seven analytically distinct themes emerged: Perceived Benefits of AI; Trust, Explainability, and Human-AI Collaboration; Governance, Ethical, and Safety Barriers; Workforce Readiness and Education Gaps; Equity, Inclusivity, and Bias Risks; Stakeholder Engagement and Co-Production; and Sustainability, Funding, and Public Trust. Findings reveal that trust in AI is not reducible to system accuracy or explainability, but shaped by power asymmetries, legitimacy deficits, and a lack of structured co-production. Educational gaps, governance ambiguities, and algorithmic bias further exacerbate stakeholder misalignment. Although reliant on secondary data, the study compensates through methodological rigour and conceptual triangulation. This study offers a novel theoretical and empirical contribution by mapping stakeholder-specific tensions and advancing a multidimensional framework for ethically aligned AI governance. It concludes that responsible AI integration in NHS diagnostic imaging depends not solely on technical innovation, but on participatory design, equitable stakeholder inclusion, and institutional trust-building across all levels of the health system.

INTRODUCTION

Background to the Research

The incorporation of artificial intelligence (AI) into NHS diagnostic imaging has been propelled by policy frameworks and technological requirements to resolve persistent challenges in healthcare delivery. This represents a significant transformation for the entire system. According to projections in the Topol Review (2019, p. 9) within the next two decades, approximately 90% of all NHS jobs will require some level of digital competency to navigate an increasingly data-driven healthcare environment. This positions AI-driven imaging at the vanguard of precision and predictive medicine. The NHS Long Term Plan (2019) sets a target for 75% of cancers to be diagnosed at stage I or II by 2028 (NHS England, 2019, p. 8). While not cited as the sole enabler, AI-driven diagnostics are expected to contribute to this goal. The NHS AI Lab was created to expedite the secure and ethical implementation of artificial intelligence in healthcare. This advanced the organisation. HM Government (2021, p. 7) National AI Strategy recognises that technical excellence alone is insufficient for sustainable transformation, stressing the importance of governance, transparency, and AI ethics in building trust and ensuring responsible innovation. The COVID-19 pandemic exposed the systemic vulnerabilities of manual diagnostic workflows, prompting an operational shift where AI transitioned from a research adjunct to a clinical necessity. Evidence from a multicentre European study demonstrated that AI-assisted CT imaging achieved 87% sensitivity and 94% specificity in detecting COVID-19, underscoring its capacity to support time-sensitive diagnostic decision-making in crisis conditions (Topff *et al.*, 2022, p. 9).

Nevertheless, although these findings suggest significant technical potential, they also expose some ongoing issues.

Born *et al.* (2022, p. 3) found that only 2.7% of AI imaging models for COVID-19 achieved high clinical maturity, evidencing a profound disconnect between technological ambition and real-world diagnostic utility.Redruello-Guerrero *et al.* (2022, p. 7) reported that AI models for COVID-19 triage in emergency departments achieved sensitivity levels between 79% and 98%. Despite this, concerns remain about their generalisability and clinical implementation due to methodological variability and limited external validation. The decision-making algorithms were unclear; hence this situation arose. As AI becomes more prevalent in diagnostic practice, hybrid intelligence models that integrate human knowledge with machine output are necessary, as this development challenges clinicians' epistemic authority. This epistemological adjustment leads to considerable ethical, professional, and legal conflicts, especially concerning accountability, data representation, and epistemological bias. Born *et al.* (2022, p. 14) caution that excluding stakeholders and neglecting inclusive design in AI development risks entrenching, rather than reducing, healthcare inequities.This study critically examines NHS stakeholder perceptions regarding the anticipated advantages and actual risks of integrating AI into diagnostic imaging, aiming to formulate evidence-based recommendations for an ethical, NHS-compliant, and sustainable implementation.

Research Question, Aim, and Objectives

Research Question: How do NHS stakeholders perceive the challenges and benefits of artificial intelligence in diagnostic imaging, and what strategies can facilitate its ethical, trustworthy, and sustainable integration?

Research Aim

To critically explore NHS stakeholders' perceptions of the challenges and benefits associated with the adoption of artificial intelligence (AI) in diagnostic imaging, and to develop evidence-informed recommendations for promoting its ethical, trustworthy, and sustainable integration within diagnostic services.

Research Objectives:

- To Critically explore NHS stakeholders' concerns regarding AI integration in diagnostic imaging workflows.
- To Identify and synthesise perceived benefits AI offers to diagnostic service quality, efficiency, and outcomes.
- To Develop evidence-informed, actionable recommendations to enhance stakeholder trust and facilitate responsible AI implementation.

Justification for the Research

This research is theoretically justified by its critical engagement with the persistent underrepresentation of multi-stakeholder, socio-technical perspectives in AI-healthcare adoption studies within NHS diagnostic imaging. While TAM has been widely applied in commercial and educational AI contexts, its integration within the socio-clinical setting of NHS imaging remains critically limited. Recent work has highlighted the importance of governance, stakeholder inclusion, and tailored implementation strategies for AI in radiography, yet theoretical application frameworks remain underexplored (Stogiannos*et al.*, 2024, p. 618). Nirapai and Leelasantitham (2024, pp. 6–9) demonstrate that radiologists' Quality of Experience (QoE) with AI-based imaging is shaped by contextual, human, and system-level factors—underscoring the need for a stakeholder-centred, socio-technical reinterpretation of TAM within clinical diagnostic settings.

Practically, the NHS faces immediate imperatives to accelerate trustworthy AI integration, highlighted by diagnostic workforce shortages and escalating imaging demands. Rainey *et al.* (2024, p. 12-13) found that 86.7% of radiographers agreed with binary AI diagnoses, and this agreement significantly correlated with trust, underscoring that successful deployment of AI in clinical imaging depends not only on technical accuracy but on alignment with human-centred trust cues. This research, by capturing stakeholder perceptions in real time, offers NHS leaders and AI developers granular insights essential for developing resilient, user-aligned implementation frameworks.

This study aligns with key national policy frameworks including the Topol Review (2019, p. 9), NHSX AI guidance (2019, p. 76), and NHS England's 2022–23 plan (2022, p. 17), all of which foreground stakeholder-centred innovation, ethical governance, and equitable digital health implementation. Al-Zahrani and Alasmari (2025, p. 31) report that 43.9% of MENA higher education institutions remain at early stages of AI adoption, highlighting persistent gaps between policy ambition and real-world integration—an insight that underscores the need for sector-specific empirical evaluations in healthcare domains. By extending Stakeholder Theory and TAM into live NHS diagnostic settings, this study not only contributes significant empirical advancements but also supports the construction of a socio-ethical infrastructure for sustainable AI deployment across NHS imaging services.

MATERIAL AND METHOD

This chapter outlines the philosophical, strategic, and procedural foundations guiding this study's investigation into stakeholder perceptions of AI integration in NHS diagnostic imaging. Recognising that AI's adoption in clinical radiology is not merely a technical shift but a socio-institutional transformation, this chapter justifies a qualitative, interpretive approach grounded in inductive reasoning. The objective is to explore how radiographers, radiologists, clinicians, managers, and patients interpret, accept, or resist AI systems—especially under conditions shaped by power hierarchies, ethical uncertainties, and policy-driven digitisation.The chapter outlines the methodological approach underpinning the study, explaining the choice of interpretivism and inductive logic over positivist or quantitative methods due to the study's exploratory nature and ethical constraints within NHS contexts. It justifies the reliance on secondary data, aligned with the conceptual framework informed by the Technology Acceptance Model (TAM) and Stakeholder Theory. The data collection strategy is defined through clear inclusion and exclusion criteria and supported by source triangulation to enhance validity. Braun and Clarke six-phase thematic analysis guides the analytical process, ensuring rigorous theme development and interpretive clarity. Ethical considerations are addressed through adherence to secondary research best practices, including responsible data handling and representational integrity.

Methodological Considerations

Justification for Selected Paradigm and Methodology

This study adopts a qualitative interpretive paradigm underpinned by inductive reasoning, as it offers an epistemologically coherent approach for capturing NHS stakeholder perceptions of AI in diagnostic imaging. To examine how radiologists, radiographers, clinicians, and managers interpret the impact of technological developments on institutional hierarchies, interpretivism provides a theoretically appropriate framework. This is grounded in the view that social realities are constructed through interaction and shaped by contextual dynamics. Tanweer et al. (2021, pp. 2–3) argue that interpretivist approaches can illuminate the hidden social norms, assumptions, and ethical complexities underlying AI systems—offering critical insight into how technologies like algorithmic decision-making are shaped by and reinforce existing power structures. Operationalising inductive reasoning through thematic analysis facilitates the identification of recurring patterns and meaning-making processes within stakeholder narratives.

Rejected Methodologies and Methods

Due to ethical considerations, time constraints for ethical approval, and an uneven effort-to-yield ratio given the study's timeline, collecting primary data was legally and methodologically rejected. Often, NHS Research Ethics Committees (RECs) require approval cycles lasting more than six months. This is particularly true for positions that deal directly with patients. Equally, quantitative methods—while statistically elegant—are epistemologically incompatible with the study's aim. Quantification cannot uncover stakeholder affect, ambivalence, or institutional misalignment that shapes real-world AI resistance. Williams (2024, pp. 3–5) cautions that AI-integrated research risks undermining interpretive inquiry by reducing rich, contextual meanings to computational artefacts—challenging the human-centred depth required in complex domains such as clinical practice and health policy. In sum, a qualitative, interpretivist, inductive approach is not only methodologically justifiable but essential for exploring how NHS stakeholders ascribe meaning to AI, navigate its risks, and articulate their vision for responsible implementation in diagnostic imaging.

Research Design

This study adopts a secondary data analysis design to explore NHS stakeholder perceptions of AI in diagnostic imaging systematically. The decision to analyse existing peer-reviewed stakeholder studies, NHS strategy documents, and clinical survey reports was driven by two principal considerations: the abundance of publicly available data and access limitations to front-line NHS personnel. Unlike primary research, this approach circumvents institutional gatekeeping while maintaining methodological rigour, allowing the researcher to synthesise stakeholder voices already captured in highly credible studies critically. Secondary data analysis is particularly suitable in healthcare when the aim is thematic convergence across complex organisational systems. As Hole (2024, pp. 3–6) argues, the effectiveness of Braun and Clarke's thematic analysis hinges not on the origin of the data but on the researcher's epistemological positioning and reflexive engagement. This study applies their six-phase model to support interpretive depth and thematic coherence in NHS stakeholder analysis. Campbell *et al.* (2021, pp. 2012–2013) affirm that reflexive thematic analysis is well-suited for applied health research due to its theoretical adaptability and emphasis on analytic transparency—qualities essential for interpretive rigor in complex clinical contexts. Thematic analysis was chosen because it can reveal buried institutional discourse meaning patterns that are concealed. Byrne (2022, pp. 1393–1395) emphasises that reflexivity and theoretical alignment are essential to achieving interpretive depth in applied thematic analysis. Building on this, the present study integrates Reflexive Thematic Analysis with TAM and Stakeholder Theory to ensure the thematic architecture critically reflects NHS actors' perspectives on AI-related challenges and enablers.

Research Methods / Procedures

Data Collection

This research employed a rigorously designed secondary data collection method, targeting peer-reviewed academic studies, NHS literature, and UK government reports published between 2020 to 2025. This decision aligns with the interpretive, inductive paradigm underpinning the study, privileging rich contextual narratives and empirically grounded stakeholder insights over numerical generalisability. It responds to two key constraints: first, limited direct access to NHS professionals due to institutional ethics hurdles; second, the abundant availability of high-quality stakeholder data in the public domain following AI policy rollouts such as the AI in Health and Care Award.

To ensure methodological transparency and credibility, a structured systematic review protocol was implemented using the PRISMA 2020 framework, enabling traceable and replicable data selection aligned with the interpretivist qualitative paradigm of this study. The initial pool consisted of 250 records, identified across a range of scholarly and institutional databases including PubMed, Scopus, Web of Science, Google Scholar, NHS Digital, NICE Evidence, NHSX publications, and the Health Education England repository. Boolean logic was applied to maximise retrieval accuracy using: ("Artificial Intelligence" OR "AI") AND ("Diagnostic Imaging") AND ("NHS") AND ("Stakeholder Perceptions") AND ("Trust" OR "Adoption" OR "Ethics" OR "Governance"). After removing 30 duplicates, 20 automation-based exclusions, and 10 irrelevant studies, 190 records were screened by title and abstract. Subsequently, 70 full-text articles were assessed for eligibility based on predefined criteria prioritising UK-based, stakeholder-focused, empirical or policy studies published between 2020 and 2025.

Following this critical appraisal, 13 empirical studies were retained. These were selected due to their direct relevance to the NHS diagnostic imaging context and their rich stakeholder narratives addressing trust, legitimacy, implementation barriers, and ethical governance—central constructs under the study's conceptual framework (TAM and Stakeholder Theory). This PRISMA-guided process enhanced thematic saturation, reduced confirmation bias, and ensured that the findings emerged from an ethically curated and theoretically congruent evidence base. The full selection process is visually illustrated in Figure 3.1 (PRISMA 2020 Flow Diagram), confirming adherence to systematic standards required for robust qualitative secondary research.

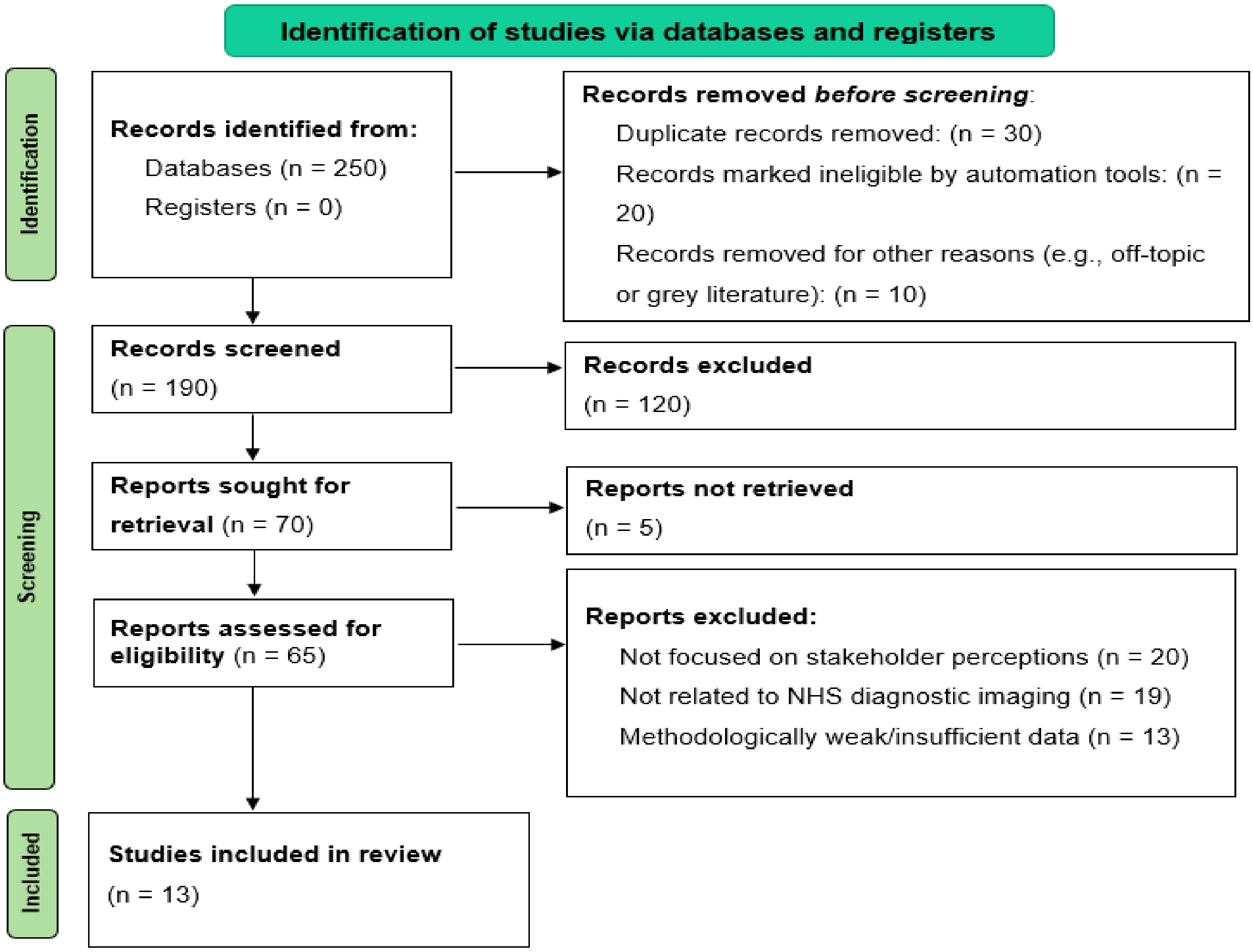

Figure 3.1: PRISMA 2020 Flow Diagram

Data Analysis

This study employed Braun and Clarke (2006, pp. 79–92) six-phase reflexive thematic analysis to interpret stakeholder perceptions of AI in NHS diagnostic imaging. This approach, grounded in interpretivist epistemology, allows for rich, context-sensitive exploration of meaning-making across stakeholder narratives. Its recursive and flexible nature is well-suited for secondary qualitative synthesis, where depth and theoretical alignment matter more than mere frequency.

Phase 1: Familiarisation with the Data: The 13 selected peer-reviewed UK-based studies were read repeatedly, with notes taken on emerging discourse patterns across radiologists, radiographers, managers, patients, and developers. Early impressions pointed to recurring dilemmas between AI optimism and professional disempowerment. For instance, discussions of algorithmic explainability often intertwined with themes of mistrust and perceived deskilling—an early signal of deeper epistemic tensions.

Phase 2: Generating Initial Codes: An inductive coding strategy was applied manually. Open codes such as *"diagnosticdisempowerment,""black-box resistance,""governance void,"* and *"co-production vacuum"* were developed directly from participant quotations and study interpretations. These codes captured stakeholder anxieties, enablers, and perceived systemic blind spots without being constrained by pre-structured categories.

Phase 3: Searching for Themes: Codes were categorised into higher-order thematic clusters reflecting conceptual patterns. For instance, *"Opacity and Trust Discontinuities"* was derived from codes related to ethical opacity, lack of explainability, and reduced clinical agency. Themes were reviewed iteratively to maintain alignment with TAM (e.g., perceived usefulness) and Stakeholder Theory (e.g., legitimacy).

Phase 4: Reviewing Themes: The provisional themes were tested against the full dataset to ensure analytic integrity. Redundant or overlapping themes were either merged or refined. A theme such as *"Equity and Bias"* was validated only when multiple sources referenced demographic underrepresentation and algorithmic injustice.

Phase 5: Defining and Naming Themes: Seven final themes were precisely defined to reflect both empirical salience and theoretical resonance. Labels such as

"Stakeholder Engagement and Co-Production" were selected to convey analytical clarity and policy relevance.

Phase 6: Producing the Report: Each theme was situated within the broader objectives and conceptual framework, enabling theoretical triangulation. Themes were not only descriptively presented but interpreted through the lenses of TAM and Stakeholder Theory to reveal deeper stakeholder-system dynamics.

DATA ANALYSIS AND INTERPRETATION

This chapter offers a critical thematic analysis of stakeholder perceptions regarding the adoption of AI in NHS diagnostic imaging, progressing from empirical patterns in diagnostic imaging to advanced theoretical frameworks. Reflexive thematic analysis was selected to offer a comprehensive, stakeholder-focused understanding that addressed the intricate socio-technical dynamics neglected by quantitative meta-aggregation. Braun and Clarke (2006, pp. 86–90) six-phase thematic analysis framework enabled the structured identification of patterns and iterative refinement of themes across the dataset. This approach facilitated systematic abstraction and conceptual layering, advancing interpretive depth throughout the analysis. It enabled stakeholder concerns, aspirations, and contextual realities to emerge without being hastily classified. Results are presented through two tiers of analysis. Initially, Table 4.1 presents the excluded results; Table 4.2 delineates the synthesised themes and directly correlates empirical insights with the research objectives. The second component involves a crucial thematic discussion utilising the Technology Acceptance Model (TAM) and Stakeholder Theory to ascertain the implications of the identified patterns. This structure preserves the integrity of empirical voices while enabling rigorous theoretical interrogation, setting the foundation for the subsequent critical discussion of how trust, governance, workforce readiness, equity, and public legitimacy shape the evolving landscape of AI integration in NHS diagnostic imaging services.

Data Analysis

Presentation of Key Findings

The Data Extraction Thematic Table 4.1 presents a systematically synthesised overview of the thirteen empirical and policy studies selected for this study's secondary data analysis. Each entry details key attributes—study title, year, research aim, methodology, sample size, key findings, thematic patterns, and alignment with the research objectives—offering a transparent and methodologically rigorous foundation for subsequent thematic interpretation. This table is integral to the study's aim of exploring NHS stakeholder perceptions of AI integration in diagnostic imaging, ensuring that each included study directly engages with relevant NHS actors (e.g., radiographers, radiologists, patients, and managers) within a UK diagnostic context. The selection spans a diversity of qualitative and mixed-method designs; where quantitative data were used, they served to enrich and contextualise the qualitative thematic synthesis. The table's structure allows readers to trace the analytic pathway from raw data to theory-aligned themes, thereby reinforcing the validity of the reflexive thematic analysis that follows. Furthermore, by explicitly mapping each study's relevance to the study's core objectives, the table supports both conceptual coherence and empirical transparency, making it a critical bridge between evidence and interpretation in the context of ethical, stakeholder-informed AI adoption across NHS imaging services.

Table 4.1: Data Extraction Thematic Table

References	Year	Research Aim/Focus	Methodology	Sample Size & Population	Key Findings	Themes/Patterns	Relevance to Objectives
Aravazhi, P. S., Ravindran, K. O., Balasubramani, K., Kamil, M., Gouthaman, K., Karki, L., Thiyagarajan, S., & Nair, A. S. (2024). Radiologists' perceptions and readiness for integrating artificial intelligence in diagnostic imaging: A survey-based study. Bioinformation. https://doi.org/10.6026/9732063002001943	2024	Explore radiologists' perceptions and readiness for AI integration in diagnostic imaging.	Quantitative (Survey)	100 practicing radiologists (greater than or equal to 1 year experience)	65.5% perceived enhanced diagnostic accuracy, 63% improved workflow, and 49% job displacement concerns; younger radiologists (less than 5 years) showed 74% readiness, and 55% supported formal AI training.	Diagnostic optimism; ethical/job concerns; generational readiness gap; demand for AI education.	Objectives 1, 2 & 3.
Chada, B. V., & Summers, L. (2022). AI in the NHS: a framework for adoption. Future Healthcare Journal, 9(3), 313–316.	2022	Develop a framework for responsible AI adoption in NHS healthcare.	Qualitative (Expert Consultation)	NHS policymakers, AI specialists (unspecified)	Proposed eight-domain framework; bias vigilance; need for data drift surveillance; clinical oversight mandatory.	Ethics and governance; operational challenges; stakeholder trust; system-wide change.	Objectives 1, 2 & 3.

Doherty, G., McLaughlin, L., Hughes, C., McConnell, J., Bond, R., & McFadden, S. (2024). Radiographer Education and Learning in Artificial Intelligence (REAL-AI): A survey of radiographers, radiologists, and students' knowledge of and attitude to education on AI. Radiography, 30, 79–87.	2023	Investigate knowledge, attitudes, and perceived educational needs of radiographers and radiologists regarding AI.	Quantitative (Survey, Conference Abstract)	The exact sample size was not disclosed for radiographers, radiologists, and dual-trained students.	80% recognised the need for enhanced AI education, 67% rated knowledge as poor to moderate, and 71% supported mandatory AI curriculum integration.	AI knowledge gaps; educational demand; curriculum reform necessity.	Objective 1 & 3.
Fazakarley, C. A., Breen, M., Leeson, P., Thompson, B., & Williamson, V. (2023). Experiences of using artificial intelligence in healthcare: a qualitative study of UK clinician and key stakeholder perspectives. *BMJ open*, *13*(12), e076950.	2023	Understand NHS healthcare professionals and key stakeholders' perceptions of AI use and barriers to its adoption.	Qualitative (Semi-structured Interviews; Thematic Analysis)	13 participants (clinicians and non-clinicians across NHS and academia)	AI is viewed as assistive; barriers included IT infrastructure gaps, data delays, trust and transparency key concerns, risks of misdiagnosis and clinician deskilling identified.	Assistive role of AI; technical barriers; human-AI trust; deskilling concerns.	Objectives 1 & 2.
Karpathakis, K., Pencheon, E., &Cushnan, D. (2024). Learning from international comparators of national medical imaging initiatives for AI development: Multiphase qualitative study. *JMIR AI*, *3*(1), e51168.	2024	Understand international use cases of national imaging platforms for AI development to inform NHS England platform design.	Multiphase Qualitative (Desk research, PESTLE analysis, Semi-structured interviews, Workshop)	13 stakeholders interviewed from 6 countries (Canada, Hong Kong, Japan, Singapore, Sweden, USA); 5 NHS AI Lab workshop participants	Identified eight major themes, 17 subcategories, and 12 policy recommendations for the NHS platform, highlighting the need for wraparound services, interdisciplinary collaboration, sustainability, public trust, and regulatory reform.	International best practices; stakeholder-centred platform design; future-proofing; commercial models; trust and sustainability.	Objective 2 & 3.
Kuo, R. Y. L., Freethy, A., Smith, J., Hill, R., Jerome, D., Harriss, E., Collins, G. S., Tutton, E., & Furniss, D. (2024). Stakeholder perspectives towards diagnostic artificial intelligence: A co-produced qualitative evidence synthesis. *EClinicalMedicine*, *71*. https://www.thelancet.com/journals/eclinm/article/PIIS2589-5370(24)00134-2/fulltext?uuid=uuid%3Adfea1c5b-cdf1-4b2f-b17d-d4985801fe2e	2024	Using the extended NASSS framework, Synthesise stakeholder views (patients, clinicians, researchers, leaders) on diagnostic AI.	Qualitative Evidence Synthesis (Systematic Review; Best-fit framework approach)	689 interviews + 402 focus group participants (across 44 studies)	Trust, transparency, regulatory oversight, data representativeness, usability, technical support, interdisciplinary collaboration, and socio-cultural attitudes were identified as key adoption drivers or barriers; an extended NASSS-AI framework was proposed.	Stakeholder-centric adoption; governance gaps; trust building; diversity inclusion; human-AI co-working models.	Objectives 1, 2 & 3.
Lip, G., Novak, A., Goyen, M., Boylan, K., & Kumar, A. (2024). Adoption, orchestration, and deployment of artificial intelligence within the National Health Service—facilitators and barriers: An expert roundtable discussion. *BJR| Artificial Intelligence*, *1*(1), ubae009.	2024	Explore facilitators and barriers to NHS-wide AI adoption and propose future strategies.	Qualitative (Expert Roundtable)	Experts from clinical, NHS management, and industry (unspecified number)	AI adoption is slowed by data fragmentation, funding gaps, and lack of national coordination; £21m AI Diagnostic Fund has been announced; case examples include Mia and Brainomix tools.	Governance and funding hurdles; need for real-world evidence; successful pilot programs.	Objective 2 & 3.
Newlands, R., Bruhn, H., Díaz, M. R., Lip, G., Anderson, L. A., & Ramsay, C. (2024). A stakeholder analysis to prepare for real-world evaluation of integrating	2024	Conduct stakeholder analysis for integrating AI algorithms into Scotland's National	Qualitative (Focus Groups and Semi-structured	32 participants (14 stakeholder groups)	Majority supportive of AI; Key advantages: quicker results, reduced	Stakeholder diversity; cautious AI optimism; demand for co-	Objectives 1, 2 & 3.

artificial intelligent algorithms into breast screening (PREP-AIR study): A qualitative study using the WHO guide. *BMC Health Services Research*, *24*(1), 569. https://doi.org/10.1186/s12913-024-10926-z		Breast Screening Service.	Interviews; Content Analysis)		workload; Main concerns: overdiagnosis, misdiagnosis, inequality, ethical accountability; 5 strategic stakeholder management approaches proposed.	produced reforms; system readiness gaps.	
NHS Transformation Directorate. (2021, June 30). *Round 3 of the Artificial Intelligence in Health and Care Award is now open*. NHS England. https://transform.england.nhs.uk/blogs/round-3-of-the-artificial-intelligence-in-health-and-care-award-is-now-open/	2021	Support adopting AI technologies in NHS to improve diagnostics, operational efficiency, and patient self-management.	Policy Initiative Report	900 applications evaluated; 80 projects funded; 70+ trial sites operational.	£140m allocated over 4 years; early results: Navenio reduced waiting times by 29%, improved productivity by 94%.	Funding AI innovation; diagnostic AI deployment; operational impact; health equity focus.	Objective 2 & 3.
Rainey, C., Bond, R., McConnell, J., Hughes, C., Kumar, D., & McFadden, S. (2024). Reporting radiographers' interaction with Artificial Intelligence—How do different forms of AI feedback impact trust and decision switching? PLOS Digital Health, 3(8), e0000560.	2024	Quantify how AI feedback types influence trust and decision-switching in reporting radiographers.	Quantitative (Experimental Survey)	12 reporting radiographers (3 from each UK nation)	22.2% perfect agreement with heatmaps; 86.7% agreement with binary feedback; decision switching rare (1.1%); trust strongly correlated to feedback agreement.	Explainability impacts trust, binary diagnosis preferred, and low switching despite AI suggestions.	Objectives 1, 2 & 3.
Rawashdeh, M. A., Almazrouei, S., Zaitoun, M., Kumar, P., & Saade, C. (2024). Empowering radiographers: A call for integrated AI training in university curricula. International Journal of Biomedical Imaging, 2024(1), 7001343.	2024	Investigate radiographers' perceptions towards AI and views on integrating AI into educational curricula.	Quantitative (Survey)	100 radiographers (UAE, included for transferable insights into workforce readiness aligned with NHS diagnostic imaging education priorities)	52% were familiar with AI; 74% found AI helpful in medicine; 98% supported AI inclusion in university training; 87% preferred AI training; COR=1.89 (male gender) and 1.87 (age 23–27).	Positive AI perception; strong demand for formal AI education; demographic predictors.	Objectives 1, 2 & 3.
Stogiannos, N., O'Regan, T., Scurr, E., Litosseliti, L., Pogose, M., Harvey, H., Kumar, A., Malik, R., Barnes, A., & McEntee, M. F. (2024). AI implementation in the UK landscape: Knowledge of AI governance, perceived challenges and opportunities, and ways forward for radiographers. Radiography, 30(2), 612–621.	2024	Explore UK radiographers' perceptions of AI governance, challenges, and opportunities for AI implementation.	Quantitative (Online Survey, Descriptive and Chi-square analysis)	88 qualified radiographers (diagnostic, therapeutic, sonographers)	56.6% lacked AI training; 63% used evaluation frameworks; 88.6% GDPR compliance; central governance and interoperability barriers.	Training deficiency; governance/validation knowledge gaps; data security concerns; demand for leadership and funding support.	Objectives 1, 2 & 3.
Sujan, M. A., White, S., Habli, I., & Reynolds, N. (2022). Stakeholder perceptions of the safety and assurance of artificial intelligence in healthcare. *Safety Science*, *155*, 105870.	2022	Explore stakeholder perceptions on safety and safety assurance of healthcare AI.	Qualitative (Semi-structured Interviews; Thematic Analysis)	26 stakeholders (patients, hospital staff, developers, regulators)	Benefits: efficiency and reduced errors; Risks: automation complacency, data bias, accountability gaps; strong demand for system-based assurance frameworks and dynamic regulation.	Socio-technical integration; regulatory evolution necessity; safety assurance demand.	Objective 1 & 3.

Synthesised Themes and Conceptual Integration

Table 4.2 presents the synthesised thematic outcomes of Braun and Clarke (2006, pp. 87–92) six-phasethematic analysis, applied to thirteen systematically selected studies that directly address stakeholder perceptions of AI adoption in NHS diagnostic imaging. The themes were identified through a rigorous, recursive process involving repeated familiarisation with the data, inductive coding, and analytical theme construction, followed by refinement through theoretical mapping to the Technology Acceptance Model (TAM) and Stakeholder Theory. Two core criteria guided theme selection: (1) empirical salience—established through recurrence and conceptual strength across diverse study contexts—and (2) theoretical resonance—determined by each theme's alignment with constructs such as perceived usefulness, trust, legitimacy, or stakeholder urgency. The resulting seven themes are not arbitrarily grouped but analytically differentiated: for instance, "Perceived Benefits of AI in Diagnostic Imaging" aggregates findings on diagnostic accuracy, speed, and workflow efficiency, while "Trust, Explainability, and Human-AI Collaboration" captures the epistemic tension between algorithmic opacity and clinical confidence. Themes such as "Governance, Ethical, and Safety Barriers" and "Equity, Inclusivity, and Bias Risks" reveal systemic impediments rooted in regulatory ambiguity, data representativeness, and algorithmic fairness. Critically, "Stakeholder Engagement and Co-Production" and "Sustainability, Funding, and Public Trust" illuminate strategic levers for future-proofing NHS AI integration. Each theme is traceably linked to the research objectives, providing a transparent logic for interpretive analysis.

Table 4.2: Data Synthesis

Synthesis Theme	Studies Supporting Theme	Critical Insights	Relevant Research Objective(s)
Perceived Benefits of AI in Diagnostic Imaging	Aravazhi*et al.* (2024); NHS Transformation Directorate (2021); Newlands *et al.* (2024)	AI integration is perceived to enhance diagnostic accuracy, workflow efficiency, and early disease detection. However, perceived benefits are often conditional on role-specific experiences and trust in system reliability.	Objective 1: Explore stakeholder perceptions
Trust, Explainability, and Human-AI Collaboration	Rainey *et al.* (2024); Doherty *et al.* (2023); Kuo *et al.* (2024)	Trust in AI systems hinges on transparency, explainability, and clear delineation of human oversight. Stakeholders prefer AI as an assistive tool rather than an autonomous decision-maker, highlighting the criticality of hybrid clinical models.	Objective 1: Explore stakeholder perceptions; Objective 2: Identify adoption barriers
Barriers: Governance, Ethical and Safety Concerns	Chada & Summers (2022); Sujan *et al.* (2022); Lip *et al.* (2024); Stogiannos*et al.* (2024)	Governance gaps, lack of regulatory clarity, liability ambiguity, and concerns around bias and fairness in AI outputs emerge as persistent barriers to adoption, undermining organisational trust and readiness.	Objective 2: Identify adoption barriers
Workforce Readiness and Education Gaps	Rawashdeh *et al.* (2024); Doherty *et al.* (2023); Stogiannos*et al.* (2024)	Significant deficiencies exist in AI literacy among healthcare professionals. Strong stakeholder demand exists for formal, mandatory AI education integrated within undergraduate and postgraduate curricula.	Objective 3: Identify strategic recommendations
Equity, Inclusivity, and Bias Challenges in AI Models	Kuo *et al.* (2024); Sujan *et al.* (2022); Newlands *et al.* (2024)	Dataset bias and lack of representative data threaten diagnostic fairness and risk exacerbating healthcare inequalities. Stakeholders emphasise the need for inclusive, ethically trained AI models.	Objective 2: Identify adoption barriers
Importance of Stakeholder Engagement and Co-Production	Newlands *et al.* (2024); Fazakarley*et al.* (2023); Karpathakis*et al.* (2024)	Co-production involving clinicians, patients, and developers enhances AI system acceptance and ethical validity. Stakeholders advocate for iterative, inclusive design processes to ensure clinical relevance and patient trust.	Objective 3: Identify strategic recommendations
Sustainability: Funding, Infrastructure, and Public Trust	Lip *et al.* (2024); Karpathakis*et al.* (2024); NHS Transformation Directorate (2021)	Sustainable AI deployment requires stable funding, national coordination, and system-wide infrastructure upgrades. Public trust remains a fragile but critical component for long-term AI success in the NHS.	Objective 2: Identify adoption barriers; Objective 3: Identify strategic recommendations

Summary of Discussion

This chapter examines stakeholder perceptions of AI adoption in the NHS Diagnostic Imaging Policy by analysing thirteen meticulously selected empirical and policy studies. Stakeholder Theory and the Technology Acceptance Model (TAM) were employed to analyse the data. They identified seven interrelated themes: governance deficiencies, stakeholder involvement, equity preparedness, sustainability readiness obstacles, perceived benefits, and workforce dynamics. Empirical findings substantiated the conditional nature of AI's asserted benefits, demonstrating that technical proficiency alone is insufficient without epistemic governance, ethical oversight, inclusive design, and a foundation of trust. Numerous findings of the study diverged from the narratives surrounding deterministic AI adoption. These disparities include persistent gaps in the workforce's AI expertise, the public's perception of legitimacy, and individuals' ability to participate in co-design. Beyond mere descriptive mapping, this multidimensional, thematic synthesis elucidated the intricate acceptance trajectories of NHS stakeholders grounded in theoretical frameworks. It demonstrated that factors beyond the perceived utility or efficiency of integration affect individuals' intentions to utilise artificial intelligence. It disclosed that relational, ethical, operational, and socio-cultural factors also play a role. This analysis validated the research objectives and considerably broadened them. The final chapter, grounded in robust empirical and theoretical foundations, will provide strategic recommendations to promote artificial intelligence's ethical, reliable, and sustainable integration into NHS diagnostic imaging pathways.

CONCLUSION

This final chapter critically synthesizes the study's findings, moving beyond description to theoretical and practical contribution. Using a secondary qualitative, interpretivist approach and Braun and Clarke's thematic analysis, the study examined stakeholder perceptions of AI in NHS diagnostic imaging through the lenses of the Technology Acceptance Model (TAM) and Stakeholder Theory. While AI is widely seen as improving diagnostic accuracy and efficiency, its acceptance is shown to be conditional on trust, explainability, governance clarity, and stakeholder inclusion. The findings challenge linear TAM assumptions by demonstrating that perceived usefulness is ineffective without legitimacy and co-production. Stakeholder concerns about bias, accountability, and training highlight that AI integration is a socio-technical and relational process rather than a purely technical one. The study proposes a hybrid TAM–Stakeholder framework for NHS AI adoption, emphasising education, participatory design, and ethical governance. Although limited by reliance on secondary UK-based literature, the study provides a rigorous, theory-informed contribution and identifies clear directions for future longitudinal, participatory, and comparative research.

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