Navigating the Barriers and Facilitators to Implementation of AI in Healthcare: A Scoping Review

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Abstract

Background

There is increasing emphasis on leveraging artificial intelligence (AI) techniques to enhance healthcare delivery and decision-making. However, despite much interest and early promise, a major challenge is translation into clinical practice. There is a shift to address the challenges of AI deployment to optimise implementation and establish strategies for effective deployment of AI technology in healthcare.

Research Question

What are the key determinants influencing effective deployment of AI technology in healthcare?

Methodology

We followed PRISMA-ScR and the Joanna Briggs Institute Methodology guidelines for scoping reviews; the research protocol was published prospectively on Open Science Framework (OSF). We searched PubMed, Cochrane, Ovid Medline, Scopus and IEEE Xplore for papers published in English from 2000, including systematic/scoping reviews and meta-analyses with full text available.

Results

The initial search was limited to AI medical imaging technology. It identified 1,511 papers, of which 523 met the eligibility criteria based on title and abstract screening. 488 papers were excluded due to context or content irrelevance, leaving 35 papers for full-text review. No systematic/scoping reviews specifically addressing the deployment of AI medical imaging solutions were identified, prompting the inclusion criteria to be broadened to encompass any study designs related to all relevant technology. Fifteen papers were included in the final scoping review.

Conclusion

The successful deployment of AI in healthcare is challenging, due to barriers which can be ethical, technological, regulatory, financial, patient and workforce-related. Facilitators to drive successful implementation include planning, organisational culture, patient involvement, stakeholder engagement, education and leadership. Awareness of the barriers and facilitators can better enable healthcare institutions to streamline the deployment of AI technology.

Keywords: Artificial Intelligence, Implementation, Healthcare, Imaging, Barriers, Facilitators

I. Introduction

There is growing emphasis on leveraging artificial intelligence (AI) techniques to enhance healthcare delivery and decision-making.[1,2] The National Health Service (NHS) Long Term Plan (2019), the strategic vision for the NHS, recognises the transformative role of AI in the digital transformation of healthcare services.[3] This is also reflected in the National Institute for Health and Care Research (NIHR) Agenda, which highlights the importance of AI in advancing healthcare research and delivery.[4]

Fracture detection serves as a key example of the potential impact of AI in medical imaging, particularly within orthopaedic care. It enables a fast, accurate diagnosis and facilitates treatment planning. Traditional methods of fracture detection rely on manual interpretation of X-ray images, which has a significant learning curve, and is prone to error among clinicians. AI algorithms have the potential to analyse images quickly and accurately to reduce error and improve efficiency.[5-7] AI applications in healthcare extend beyond just medical imaging though, encompassing diagnostics, predictive analytics, and workflow optimisation. While fracture detection remains a prominent use-case, broader applications in clinical decision support, patient stratification, and surgical planning also merit consideration.[8]

In traditional fields of medical research, there is a 17-year lag between the generation of evidence and its integration into clinical practice.[1] A recent review on AI fracture detection systems identified 21 commercially-available AI products with Conformité Européenne (CE)/Food and Drug Administration (FDA) approval, however there is little uptake of this technology across the 215 UK hospital trusts.[9] As AI imaging tools continue to be developed and refined, their translation into clinical practice is slow.

AI in healthcare lacks a standardised implementation pathway, but its development pipeline follows a structured progression from inception through validation, regulatory approval, and clinical integration. Given the high-stakes nature of healthcare, AI must meet exceptionally high precision and reliability standards to ensure patient safety and clinical effectiveness. However, unlike traditional tools, there is no universal accuracy benchmark for AI models, leading to potential inconsistencies in performance.[10] Furthermore, implementation differs across healthcare systems; the NHS, as a publicly-funded model, requires extensive validation and economic evaluation before adoption, whereas more market-driven systems, such as the US, often allow for faster adoption but introduce greater variability across institutions.[3,4]

Understanding the systemic barriers and facilitators shaping AI adoption is critical, as regulatory policies, clinical workflows, and financial constraints influence implementation differently across settings. Identifying these challenges is essential to bridging the knowledge-to-action gap and ensuring AI solutions can be effectively integrated into clinical practice.[2]

This scoping review aims to map the available evidence on factors influencing the implementation of AI in healthcare. The authors aim to identify and categorise the key barriers and facilitators associated with deploying these AI solutions within NHS clinical pathways. Additionally, we seek to explore strategies for effectively integrating AI solutions into routine clinical practice, with the ultimate goal of informing the development of a comprehensive framework for their successful deployment within the NHS.

II. Methodology

The initial research question aimed to explore the key determinants influencing the effective deployment of AI medical imaging solutions. However, due to the limited availability of high-quality evidence specific to medical imaging, the scope of the review was broadened to encompass AI applications across all healthcare domains. This shift was made to ensure a comprehensive analysis of the barriers and facilitators to AI implementation. For transparency, this change has been documented, reflecting the evolving focus of the review to address AI integration in healthcare more broadly.

Research Question

What are the key determinants influencing the effective deployment of AI technology in healthcare?

Scoping Review Approach

Given the broad and exploratory nature of this research area, a scoping review approach was deemed appropriate for several reasons:

1. Mapping the extent and nature of the literature: This review does not aim to answer specific clinical questions but comprehensively map AI implementation science in healthcare. A scoping review explores diverse evidence sources, including peer-reviewed and grey literature, to provide a holistic understanding of the research landscape.
2. Identifying key concepts and themes: The review seeks to identify factors influencing AI deployment and inform a gold-standard framework for NHS integration. A scoping review highlights relevant themes and patterns across literature, offering insights into the factors affecting implementation.
3. Addressing heterogeneity of literature: The literature on AI implementation in healthcare is expected to be heterogeneous, encompassing various study designs, methodologies, and contexts. A scoping review allows for the inclusion of diverse sources of evidence, regardless of study design or methodological rigor.
4. Informing future research and policy development: By synthesising AI implementation evidence, this review informs future research, policy, and clinical guidelines. The review findings will provide a foundation for further investigation and guide strategic decision-making.

Protocol

The research plan and protocol were formulated in accordance with the Joanna Briggs Institute Methodology and Preferred Reporting Items for Systematic Reviews and Meta-analysis Protocols Guidelines for Scoping Reviews (PRISMA-ScR). A detailed checklist has been completed to ensure compliance. This methodological framework served as the cornerstone for the development of our comprehensive research strategy, ensuring adherence to established standards of rigor and transparency in the conduct of our scoping review. For transparency, the protocol was published on the Open Science Framework (OSF).[11-13]

Eligibility Criteria

The eligibility criteria for the sources of evidence are included in Table 1.

Table 1 - Eligibility Criteria

Timeframe	Papers published from 2000 onwards will be included in the analysis. This timeframe ensures the review covers recent advancements and developments in AI solutions relevant to the research question.
Language	Only papers published in English were considered for inclusion. Limiting the review to English language publications helps ensure consistency in data extraction and analysis, as well as accessibility to the research team.
Publication Status	In the first instance, only scoping reviews, systematic reviews and meta-analyses were included. But this was broadened to all peer-reviewed journal articles and scholarly papers to capture a comprehensive range of evidence and perspectives on the implementation of AI medical imaging solutions in orthopaedic surgery.
Full Text Availability	Only literature with full text available was included.

Search Strategy and Screening

We searched PubMed, Cochrane Library, Ovid MEDLINE, Scopus and IEEE Xplore. The full search strings used for each database are available in Appendix 1.

Search Strings

For each database, the search strategy utilised a combination of keywords, Boolean operators, and Medical Subject Headings (MeSH) terms. The search strings were tailored to the specific indexing syntax and formatting of each database.

The search strategy was intentionally designed to focus on key implementation science concepts relevant to AI adoption in healthcare. By including terms such as "Implementation science," "Barriers," "Facilitators," and "Determinants," we aimed to extract literature that specifically discusses the practical challenges and enablers of AI integration. This approach helped manage the volume of retrieved studies while ensuring the inclusion of those most relevant to our research objectives.

Screening Process

EndNote (Clarivate) was used for deduplication and screening.

Title and Abstract Screening

Two independent reviewers screened the titles and abstracts of the citations against the predefined inclusion criteria. Discrepancies were resolved through discussion, and a third reviewer was consulted if consensus could not be reached.

Full-Text Assessment

Full texts of citations that passed the title and abstract screening were independently assessed by two reviewers. Discrepancies were resolved through discussion, with a third reviewer making the final decision if necessary.

III. Results

Selection of Sources of Evidence

The process of screening and selecting papers for the scoping review involved several steps; the Population, Concept, Context (PCC) framework was used as the guide (Table 2). A total of 1,511 papers were identified through the multiple database searches. The PRISMA flowchart (Fig 1) details the identification and screening process. Full-text screening was conducted amongst 35 papers, though all 35 were excluded due to a lack of AI medical imaging solution context/implementation science thematic analysis/level 1 evidence. Due to the limited availability of high-level evidence, the research team broadened the inclusion criteria to include papers of all levels of evidence and AI applications in broader healthcare contexts. This resulted in the identification and inclusion of 15 papers for the scoping review. Data extraction variables included AI implementation barriers, facilitators and the application/healthcare context (Table 3).

Only one article presented a discrepancy during the screening phase, which was resolved through discussion between reviewers. Thereafter, there was unanimous agreement on the inclusion of all 15 articles for detailed analysis.

Table 2 - PCC Framework

	Inclusion	Exclusion
Population	• Humans • Musculoskeletal pathology • Orthopaedic use-case	• Animals • Non-orthopaedic use-case
Concept	• System with Machine Learning/AI component • Implemented in healthcare settings with medical imaging relevance • Traditional medical imaging / diagnostic practices	• System without Machine Learning / AI component • Groups not falling within the scope of this investigation
Context	• Implementation evaluation • Implementation barriers • Implementation facilitators • Economic benefits, process improvement, treatment outcomes, etc.	• Papers with no relevant implementation outcome measures

Table 3 - Evidence Data Charting of Barriers and Facilitators to AI Implementation

Study	**Year**	**Study Design**	**Journal**	**Application & Context**	**Barriers**	**Facilitators**
Ahmed et al.[14]	2023	Systematic Review	Cureus	• Endoscopic diagnostics • Liver disease diagnosis & treatment • Radiology, oncology, cardiac imaging • Predictive Analytics • Mental Health – Precision psychiatry, suicide prediction • Diabetic retinopathy screening • Skin cancer detection	• Ethical • Technological • Liability and regulatory • Workforce • Social • Patient Safety	
Ali et al.[15]	2023	Systematic Review	Journal of Innovation and Knowledge	• Decision Support & Diagnostics • Medical Imaging • Smart Wearables • AI treatment algorithms • Robotic surgery • VR/AR training • AI Telemedicine	• Data digitisation and consolidation • Data availability • Privacy • Legal • Regulation • Decision errors • Treatment errors • Data errors	
Hogg et al.[16]	2023	Systematic Review	Journal of Medical Internet Research	• Medical Imaging & Diagnosis • Clinical Decision Support • Robotic-assisted surgery • AR/VR for surgical training • Algorithmic Prediction • AI in Public & Mental Health • Telemedicine & Digital Health		• Promoting engagement of 5 stakeholder groups: 1. Developers 2. Health care professionals 3. Health care managers and leaders 4. Patients, carers and the public 5. Regulators and policy makers • Planning • Education • Monitoring • Transparency • Accountability
Al Hashmi et al.[17]	2020	Systematic Review	Advances in Intelligent Systems and Computing	• Medical Diagnosis • Medical Imaging • Predictive analytics • Decision support tools. • Health Data Analysis		• Technology Acceptance Model: 1. Perceived Usefulness 2. Perceived ease of use

						• Promoting stakeholder satisfaction • Developing user and patient trust • Education
Gama et al.[18]	2022	Scoping Review	Journal of Medical Internet Research	• Emergency Triage Decision Support • Surgical Decision-making • Skin cancer screening • Oncology Diagnosis	• Technology • User Knowledge • Regulation • Ethics – population equity or discrimination • Implications of human-error	• Organisational Culture – readiness to change and capacity to innovate • Education to encourage acceptability - value proposition
Chomutare et al.[19]	2022	Scoping Review	International Journal of Environmental Research and Public Health	• Workflow Optimisation • Sepsis Prediction & Management • Delirium Risk Assessment • Clinical Decision Support • Diabetic Retinopathy Screening • Medical Imaging • Surgical Robotics	• Regulation and Law • Evaluation and testing • Interpretability • Interoperability • Trust • Integration • Cost	• Healthcare demand • Involvement • Planning • Adaptability • Culture • Education of workforce
Bajgain et al.[20]	2023	Scoping Review Protocol	BMJ Open	• Clinical Decision Support	• Ethical • Legal • Data- related (integration, trust and privacy) • Transparency • Lack of proper regulation (liability and accountability) • Usability	• Stakeholder engagement • Communication • Education • Champions and designated change leaders
Davis et al.[21]	2020	Observational	Current Problems in Diagnostic Radiology	• CT Imaging for Intracranial Haemorrhage	• Evaluation and testing • Trust	
Petitgand et al.[22]	2020	Interpretive Qualitative	Studies in Health Technology and Informatics	• Clinical Decision Support	• Data Interoperability • Usability • Reporting • Trust in the technology • Ethical • Liability/regulatory • Workforce resistance • Social acceptance	• Stakeholder Involvement • Organisational policy • Cultural readiness for change

					• Patient safety	
Alexander et al.[23]	2020	Interpretive Qualitative	Journal of the American College of Radiology	• Medical Imaging	• Financial implications • Ethical • Technological • Liability • Regulatory red tape • Clinician engagement/ slow adoption	• Public engagement • Stakeholder involvement
Wolff et al.[24]	2021	Literature Review	Frontiers of Digital Health	• Medical Imaging • Prostate Cancer Imaging • Breast & Lung Cancer Detection • Personalised Medicine Optimisation • Smoking Cessation • Diabetes Management • Electronic Health Records • QALY-based AI Assessments	• Data – "blackbox" phenomenon • Privacy • Policy and regulation	• "Privacy by design" technology • Clear accountability, liability, and culpability • Clinical and economic impact measurement – effect on QALYs
Brady et al.[25]	2020	Narrative	Diagnostics (Basel)	• Medical Imaging	• Transparency • Interpretability • Explainability • Ethical and Privacy • Liability • Workforce Disruption • Technological – overfitting	
Ho et al.[26]	2019	Narrative	Clinical Radiology	• Medical Imaging	• Ethical • Technological – "blackbox phenomenon" (transparency) • Liability and regulatory • Workforce and Stakeholder Engagement	
He et al.[27]	2019	Narrative	Nature	• Medical Imaging • Disease risk and progression • Workflow Optimisation • Triage and Screening • Clinical Decision Support	• Data Privacy • Transparency • Patient safety • Financial Issues • Policy and regulation	• Integration into existing clinical workflows • Stakeholder engagement • Workforce education

Pesapane et al.[28]	2018	Narrative	Insights into Imaging	• Medical Imaging	• Ethical – data protection and cybersecurity • Technological • Liability - accountability • Regulatory • Patient safety	

IV. Discussion

There was limited high-quality evidence specifically focused on AI implementation in medical imaging. Therefore, this review broadened its scope to AI deployment in healthcare overall. This approach enabled a more comprehensive analysis of key barriers and facilitators influencing AI adoption across all healthcare applications rather than focusing solely on imaging.

Barriers

Ethical

Ethical concerns were prevalent across the literature. Ahmed et al.[14] (2023) identified key issues, including privacy, conflicts of interest, and algorithmic fairness. AI's ethical implications include bias, stakeholder conflicts of interest and safeguarding patient confidentiality. Bias can perpetuate disparities, leading to unequal treatment if AI models are trained on skewed datasets. This necessitates bias detection and mitigation strategies. Additionally, informed consent raises questions about how much patients should know about AI's decision-making. Continuous oversight and robust ethical frameworks are crucial. Gama et al.[18] (2022) and Ho et al.[26] (2019) echoed these concerns, emphasising the risks of discrimination and challenges in maintaining transparency and trust.

Technological

Technological barriers include data quality, standardisation, and integration challenges. Ahmed et al.[14] (2023) and Gama et al.[18] (2022) highlighted difficulties in interoperability, usability, and infrastructure. AI requires large volumes of high-quality data, yet healthcare data is often fragmented or inconsistent. Ali et al.[15] (2023) noted that issues with digitisation, availability, and errors impact decision-making. The "black box" phenomenon, where AI decision-making lacks transparency, remains a major challenge.[24,26] Advancing explainable AI (XAI) is essential for ensuring clinician trust and seamless integration into clinical practice.

Regulatory

The evolving regulatory landscape remains fragmented and complex, slowing innovation. The lack of harmonised international standards creates uncertainty, as highlighted in the literature. AI in healthcare requires clear frameworks for liability, accountability, and compliance.[14,19,20] Ali et al.[15] (2023) and Alexander et al.[23] (2020) noted hurdles such as inadequate regulation and bureaucratic red tape, delaying adoption. Regulatory bodies must develop comprehensive guidelines that address the specificities of AI technologies, such as continuous learning and adaptive algorithms. These guidelines should delineate clear pathways for the approval, monitoring, and post-market surveillance of AI tools. Additionally, the establishment of liability frameworks is critical to define accountability in case of errors or adverse outcomes associated with AI-driven decisions. Engaging with regulators early can align innovations with expectations, facilitating smoother approvals.

Workforce Resistance

Healthcare workforce readiness is crucial for AI adoption. Ahmed et al.[14] (2023) and Ho et al.[26] (2019) discussed barriers, including fears of job displacement. Addressing these fears through clear communication about AI's augmentative role can help. Involving healthcare professionals in AI development ensures alignment with clinical needs. Many lack familiarity and confidence in AI, leading to resistance. Training programs, including practical AI applications and continuous professional development, are essential. Alexander et al.[23] (2020) noted slow clinician engagement as a challenge. Workforce disruption and stakeholder engagement concerns were also highlighted by Brady et al.[25] (2020).

Patients and the Public

Public trust is key to AI adoption. Transparency about AI's functions and benefits garners trust. Health literacy programs educating patients about AI can demystify technology. Social barriers, including health inequalities, were noted by Ahmed et al.[14] (2023) and Petitgand et al.[22] (2020). Engaging vulnerable populations and promoting inclusivity ensures equitable AI access. The evidence highlights the importance of failsafe mechanisms and AI explainability. Involving patients in AI design ensures solutions are patient-centered. AI must address diverse needs and prioritise patient safety through rigorous testing to avoid automation bias and other risks.

Financial and Costs

Financial barriers hinder AI adoption due to high upfront costs for software, infrastructure, and staff training. Ongoing maintenance and workflow integration further increase costs. Despite AI's efficiency potential, real-world cost-effectiveness analyses are scarce.[23] Voets et al.[29] (2022) noted existing health economic evaluations focus on direct costs rather than long-term financial impacts. Addressing this gap through robust cost-benefit analyses is essential for justifying AI investments. Strategic planning and funding through public and private initiatives can support implementation. Developing scalable, cost-effective AI solutions tailored to healthcare settings will enhance adoption and sustainability.[27]

Facilitators

Stakeholder Engagement

Hogg et al.[16] (2023) emphasised the importance of involving five main stakeholder groups: developers, healthcare professionals, healthcare managers, patients/the public and policymakers/regulators. Bajgain et al.[20] (2023) and Alexander et al.[23] (2020) also stressed stakeholder engagement's role in AI adoption. Continuous collaboration fosters trust, addresses concerns, and ensures AI solutions meet the needs of all. Stakeholder involvement throughout the AI pipeline—development to deployment—ensures practicality and effectiveness, aligning AI tools with clinical workflows and patient needs.

Planning

Thorough planning ensures structured AI integration in healthcare. It includes developing roadmaps, setting clear timelines, defining responsibilities, managing risks, allocating resources, and maintaining stakeholder communication. Iterative adjustments, pilot testing, and scaling optimise AI deployment strategies. Such planning manages expectations, mitigates challenges, and ensures successful AI adoption.[16-19]

Education

Educating the workforce on AI's benefits amplifies acceptance and readiness for change. Tailored training should address different stakeholder needs, ensuring effective AI use. Simulation training, pilot programs, and continuous learning build AI confidence. Integrating AI education into medical curricula prepares future healthcare professionals. Practical AI experience is essential for successful clinical implementation.[16-20]

Organisational Culture

Gama et al.[18] (2022) and Petitgand et al.[22] (2020) discussed the significance of an organisational culture that is ready to innovate and embrace change. Policies promoting transparency, accountability, and stakeholder involvement create a conducive AI environment. Clear policies ensure regulatory compliance and facilitate AI adoption. Encouraging experimentation and recognising innovation motivates staff to embrace AI technologies.

Monitoring

Continuous monitoring ensures AI systems function correctly and ethically. "Privacy by design" integrates data protection from the outset. Implementing accountability frameworks maintains trust and regulatory compliance.[16] Regular audits and feedback loops identify and rectify issues promptly. Ongoing AI performance monitoring, including real-world validation and post-market surveillance, ensures reliability and safety.[24]

Workflow Integration

Effective AI integration into clinical workflows is essential. Understanding existing clinical practices helps AI augment rather than disrupt efficiency. Collaboration between developers and clinicians ensures seamless integration. Customising AI tools for specific settings improves usability. He et al.[27] (2019) emphasised that seamless integration reduces resistance, making AI adoption easier for healthcare providers.

Acceptability

Ensuring AI solutions are user-friendly and meet healthcare needs promotes adoption. Al Hashmi et al.[17] (2020) highlighted the Technology Acceptance Model, which focuses on perceived usefulness and ease of use. Usability testing and iterative design refine AI solutions. Highlighting successful case studies and providing robust evidence of AI's benefits can enhance acceptance. Engaging users throughout development ensures AI is practical and effective.[30]

Change Leaders

AI champions and designated change leaders are crucial for overcoming resistance and driving implementation. Respected professionals with expertise in clinical practice and AI can bridge gaps between developers and end-users. Bajgain et al.[20] (2020) highlighted their role in advocacy, training, and promoting AI benefits. Champions facilitate smoother AI adoption by addressing concerns and driving engagement.

Essential Determinants

Table 4 provides a concise summary of the core determinants influencing AI implementation in healthcare, encompassing both barriers and facilitators identified through the extensive literature scrutinised in this scoping review. These determinants highlight the key challenges that hinder adoption and the critical enablers that can drive successful integration of AI technology into clinical practice.

Table 4 - Core Determinants of AI Implementation

Essential Barriers	**Essential Facilitators**
Ethical	Stakeholder Engagement
Technological	Planning
Regulatory	Education
Financial	Workflow Integration
Patient Factors	Organisational Culture
Workforce Resistance	Leadership

V. Limitations

Restricting the review to English-language publications introduced a language bias, potentially missing key international contributions. The requirement for full-text availability may have excluded valuable yet inaccessible studies. Most critically, the extremely specialised nature of the topic resulted in no studies being identified initially; although we broadened our criteria to encompass all peer-reviewed articles. This highlights the challenges in researching cutting-edge topics where existing literature is sparse, necessitating a broader and more flexible approach in search criteria to capture a wider array of studies. Nevertheless, the broader context means our findings are generally applicable to the implementation of all AI technology. However, caution is advised, as specific nuances may emerge in different applications.

VI. Future Directions

It is imperative to focus on identifying and evaluating key determinants influencing AI implementation. This can be effectively achieved through a robust mixed methods sequential exploratory design, utilising a structured determinant framework such as the Consolidated Framework for Implementation Research (CFIR).[31] Structured focus groups and interviews with stakeholders, including clinicians, policymakers, developers, managers, and patients, will uncover insights into the specific challenges and enablers regarding the adoption of the specific AI technology, in the NHS. These qualitative methods will offer a detailed understanding of stakeholder perspectives and contextual factors. An economic evaluation is necessary to understand the financial implications of integrating the technology within healthcare systems; this will help appraise the cost-effectiveness and financial viability of the technology.

Insights from these research phases will inform the development of an effective implementation strategy, including identifying specific barriers and facilitators, assessing financial implications, and creating a gold-standard framework to accelerate successful AI integration within NHS clinical pathways.

VII. Conclusion

The intersection of artificial intelligence and implementation science offers vast potential, yet further research is essential to bridge the gap between AI development and real-world deployment. As AI continues to shape healthcare, evidence on effective implementation remains limited. With significant disparities between innovation and adoption, particularly within the NHS, the critical challenge lies in translating AI research into practical clinical solutions. While efforts to address these challenges are emerging, there remains a pressing need for strategies that accelerate seamless and effective integration into clinical workflows.

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Appendix 1

PubMed
("Artificial intelligence"[Title/Abstract] OR "AI"[Title/Abstract] OR "Machine learning"[Title/Abstract]) AND ("Radiograph"[Title/Abstract] OR "XR"[Title/Abstract] OR "Imaging"[Title/Abstract]) AND ("Implementation science"[Title/Abstract] OR "Implementation"[Title/Abstract] OR "Barriers"[Title/Abstract] OR "Facilitators"[Title/Abstract] OR "Determinants"[Title/Abstract]) AND ("Healthcare"[Title/Abstract] OR "Surgery"[Title/Abstract] OR "Orthopaedics"[Title/Abstract] OR "Orthopaedic surgery"[Title/Abstract])
Cochrane Library
("Artificial intelligence" OR "AI" OR "Machine learning") AND ("Radiograph" OR "XR" OR "Imaging") AND ("Implementation science" OR "Implementation" OR "Barriers" OR "Facilitators" OR "Determinants") AND ("Healthcare" OR "Surgery" OR "Orthopaedics" OR "Orthopaedic surgery")
Ovid MEDLINE
((Artificial intelligence OR AI OR Machine learning).ti,ab.) AND (Radiograph OR XR OR Imaging).ti,ab. AND (Implementation science OR Implementation OR Barriers OR Facilitators OR Determinants).ti,ab. AND (Healthcare OR Surgery OR Orthopaedics OR Orthopaedic surgery).ti,ab.
Scopus
(TITLE-ABS("Artificial intelligence" OR "AI" OR "Machine learning")) AND (TITLE-ABS("Radiograph" OR "XR" OR "Imaging")) AND (TITLE-ABS("Implementation science" OR "Implementation" OR "Barriers" OR "Facilitators" OR "Determinants")) AND (TITLE-ABS("Healthcare" OR "Surgery" OR "Orthopaedics" OR "Orthopaedic surgery"))
IEEE Xplore
(("Artificial intelligence" OR "AI" OR "Machine learning") AND ("Radiograph" OR "XR" OR "Imaging") AND ("Implementation science" OR "Implementation" OR "Barriers" OR "Facilitators" OR "Determinants") AND ("Healthcare" OR "Surgery" OR "Orthopaedics" OR "Orthopaedic surgery"))

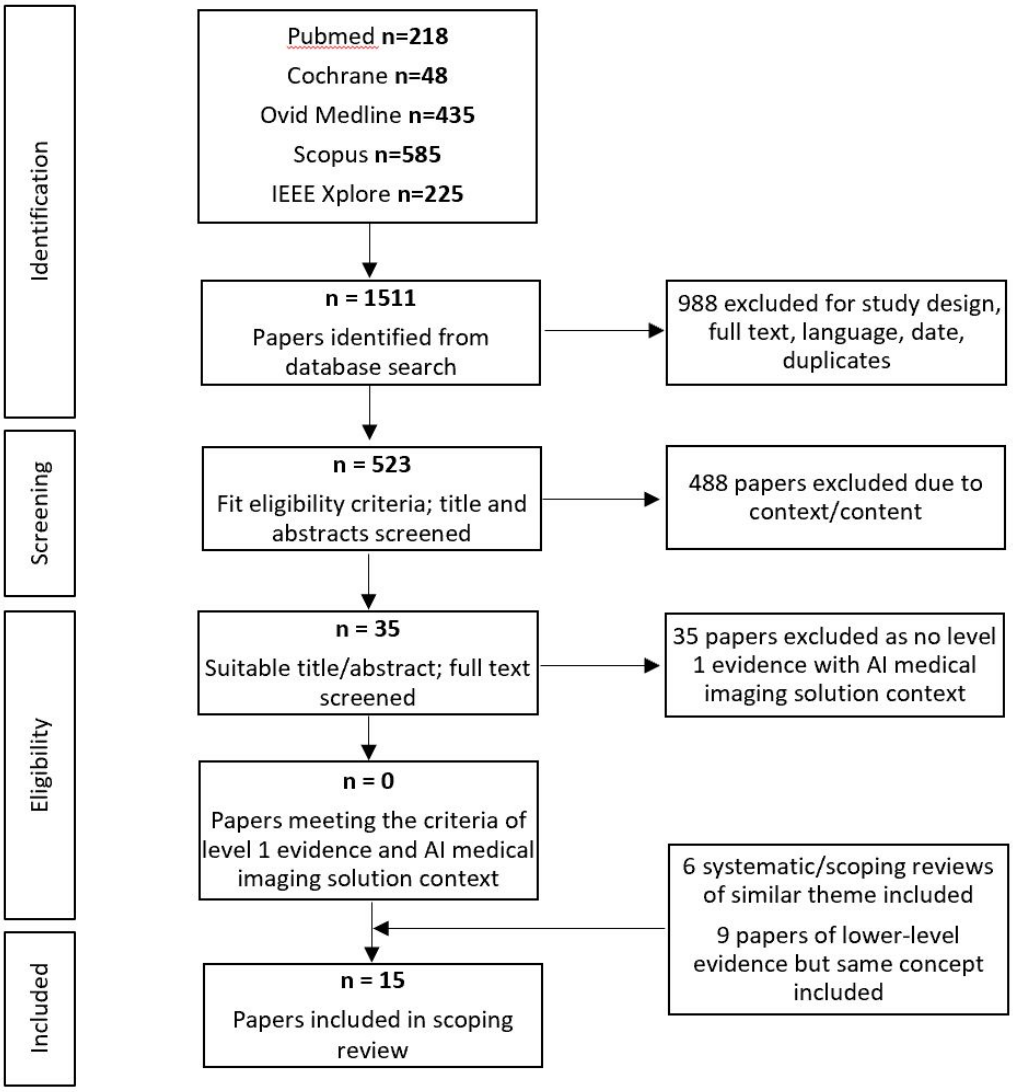

Figure 1 - PRISMA Flowchart

Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
TITLE			
Title	1	Identify the report as a scoping review.	Refer to Title
ABSTRACT			
Structured summary	2	Provide a structured summary that includes (as applicable): background, objectives, eligibility criteria, sources of evidence, charting methods, results, and conclusions that relate to the review questions and objectives.	Refer to Abstract
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known. Explain why the review questions/objectives lend themselves to a scoping review approach.	1
Objectives	4	Provide an explicit statement of the questions and objectives being addressed with reference to their key elements (e.g., population or participants, concepts, and context) or other relevant key elements used to conceptualize the review questions and/or objectives.	3
METHODS			
Protocol and registration	5	Indicate whether a review protocol exists; state if and where it can be accessed (e.g., a Web address); and if available, provide registration information, including the registration number.	4 & 18
Eligibility criteria	6	Specify characteristics of the sources of evidence used as eligibility criteria (e.g., years considered, language, and publication status), and provide a rationale.	4
Information sources*	7	Describe all information sources in the search (e.g., databases with dates of coverage and contact with authors to identify additional sources), as well as the date the most recent search was executed.	4
Search	8	Present the full electronic search strategy for at least 1 database, including any limits used, such that it could be repeated.	Refer to Appendix 1; 21
Selection of sources of evidence†	9	State the process for selecting sources of evidence (i.e., screening and eligibility) included in the scoping review.	5
Data charting process‡	10	Describe the methods of charting data from the included sources of evidence (e.g., calibrated forms or forms that have been tested by the team before their use, and whether data charting was done independently or in duplicate) and any processes for obtaining and confirming data from investigators.	5
Data items	11	List and define all variables for which data were sought and any assumptions and simplifications made.	Refer to Table 3
Critical appraisal of individual sources of evidence§	12	If done, provide a rationale for conducting a critical appraisal of included sources of evidence; describe the methods used and how this information was used in any data synthesis (if appropriate).	N/A

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
Synthesis of results	13	Describe the methods of handling and summarizing the data that were charted.	5
RESULTS			
Selection of sources of evidence	14	Give numbers of sources of evidence screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally using a flow diagram.	Refer to Figure 1
Characteristics of sources of evidence	15	For each source of evidence, present characteristics for which data were charted and provide the citations.	Refer to Table 3
Critical appraisal within sources of evidence	16	If done, present data on critical appraisal of included sources of evidence (see item 12).	N/A
Results of individual sources of evidence	17	For each included source of evidence, present the relevant data that were charted that relate to the review questions and objectives.	Refer to Table 3
Synthesis of results	18	Summarize and/or present the charting results as they relate to the review questions and objectives.	Refer to Table 3
DISCUSSION			
Summary of evidence	19	Summarize the main results (including an overview of concepts, themes, and types of evidence available), link to the review questions and objectives, and consider the relevance to key groups.	11-16
Limitations	20	Discuss the limitations of the scoping review process.	16
Conclusions	21	Provide a general interpretation of the results with respect to the review questions and objectives, as well as potential implications and/or next steps.	17
FUNDING			
Funding	22	Describe sources of funding for the included sources of evidence, as well as sources of funding for the scoping review. Describe the role of the funders of the scoping review.	Title Page

JBI = Joanna Briggs Institute; PRISMA-ScR = Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews.
* Where *sources of evidence* (see second footnote) are compiled from, such as bibliographic databases, social media platforms, and Web sites.
† A more inclusive/heterogeneous term used to account for the different types of evidence or data sources (e.g., quantitative and/or qualitative research, expert opinion, and policy documents) that may be eligible in a scoping review as opposed to only studies. This is not to be confused with *information sources* (see first footnote).
‡ The frameworks by Arksey and O'Malley (6) and Levac and colleagues (7) and the JBI guidance (4, 5) refer to the process of data extraction in a scoping review as data charting.
§ The process of systematically examining research evidence to assess its validity, results, and relevance before using it to inform a decision. This term is used for items 12 and 19 instead of "risk of bias" (which is more applicable to systematic reviews of interventions) to include and acknowledge the various sources of evidence that may be used in a scoping review (e.g., quantitative and/or qualitative research, expert opinion, and policy document).

From: Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMAScR): Checklist and Explanation. Ann Intern Med. 2018;169:467–473. doi: 10.7326/M18-0850.