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Understanding the factors influencing acceptability of AI in medical imaging domains among healthcare professionals: A scoping review

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ABSTRACT

Background: Artificial intelligence (AI) technology has the potential to transform medical practice within the medical imaging industry and materially improve productivity and patient outcomes. However, low acceptability of AI as a digital healthcare intervention among medical professionals threatens to undermine user uptake levels, hinder meaningful and optimal value-added engagement, and ultimately prevent these promising benefits from being realised. Understanding the factors underpinning AI acceptability will be vital for medical institutions to pinpoint areas of deficiency and improvement within their AI implementation strategies. This scoping review aims to survey the literature to provide a comprehensive summary of the key factors influencing AI acceptability among healthcare professionals in medical imaging domains and the different approaches which have been taken to investigate them.

Methods: A systematic literature search was performed across five academic databases including Medline, Cochrane Library, Web of Science, Compendex, and Scopus from January 2013 to September 2023. This was done in adherence to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines. Overall, 31 articles were deemed appropriate for inclusion in the scoping review.

Results: The literature has converged towards three overarching categories of factors underpinning AI acceptability including: user factors involving trust, system understanding, AI literacy, and technology receptiveness; system usage factors entailing value proposition, self-efficacy, burden, and workflow integration; and socio-organisational-cultural factors encompassing social influence, organisational readiness, ethicality, and perceived threat to professional identity. Yet, numerous studies have overlooked a meaningful subset of these factors that are integral to the use of medical AI systems such as the impact on clinical workflow practices, trust based on perceived risk and safety, and compatibility with the norms of medical professions. This is attributable to reliance on theoretical frameworks or ad-hoc approaches which do not explicitly account for healthcare-specific factors, the novelties of AI as software as a medical device (SaMD), and the nuances of human-AI interaction from the perspective of medical professionals rather than lay consumer or business end users.

Conclusion: This is the first scoping review to survey the health informatics literature around the key factors influencing the acceptability of AI as a digital healthcare intervention in medical imaging contexts. The factors identified in this review suggest that existing theoretical frameworks used to study AI acceptability need to be modified to better capture the nuances of AI deployment in healthcare contexts where the user is a healthcare professional influenced by expert knowledge and disciplinary norms. Increasing AI acceptability among medical professionals will critically require designing human-centred AI systems which go beyond high algorithmic performance to consider accessibility to users with varying degrees of AI literacy, clinical workflow practices, the institutional and deployment context, and the cultural, ethical, and safety norms of healthcare professions. As investment into AI for healthcare increases, it would be valuable to conduct a systematic review and meta-analysis of the causal contribution of these factors to achieving high levels of AI acceptability among medical professionals.

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1. Introduction and motivation

It is anticipated that the adoption of AI technology in the medical imaging industry will be a paradigm shifting trend which will radically increase the speed, quality, and value of work done by healthcare professionals [1]. AI refers to computer systems that are capable of performing tasks that ordinarily require human intelligence [2]. Machine learning is a subset of AI which involves algorithms autonomously extracting patterns and trends embedded in data to produce a mathematical model that can provide predictive outputs based on new, unseen inputs [2]. Medical AI systems of this nature have wide-ranging use cases to support clinical decision-making and optimise workflows to improve productivity and clinical outcomes [1,3,4]. Some examples of this include interpreting medical images to generate diagnostic recommendations and personalised treatment plans which act as a second medical opinion and form the basis of pre-populated preliminary medical reports, triaging patient cases based on severity, predicting patient admissions to inform resource and staffing allocation, and scheduling patient consultations. Hence, AI promises to be a valuable tool in addressing the systemic issues of increasing diagnostic imaging workloads and human error which threaten to compromise the quality of care provided by healthcare professionals in medical imaging contexts [5,6]. This is especially so for the radiology discipline which has been at the pioneering forefront of innovating and introducing AI in medical practice compared to other imaging fields [1]. Studies indicate that the average radiologist needs to interpret an image every three to four seconds in an eight-hour workday to satisfy workload requirements and that it is unlikely this onerous workload will stabilise or decline in the foreseeable future [7]. Meanwhile, misdiagnosis rates range between 3% and 5% in daily practice and is around 30% in retrospective radiologic studies [5]. The Institute of Medicine estimates that in the United States alone human error is responsible for more than 12 million misdiagnoses among adults and for 251,000 patient deaths annually [8].

Past studies and reviews concerning medical AI systems in healthcare imaging domains have largely focused on gathering evidence for the utility and safety of AI to demonstrate their feasibility (or lack thereof) for real-world deployment particularly where it concerns diagnostic use cases [1,3,4,9,10]. This often involves evaluating the technical performance of AI systems using diagnostic accuracy metrics (e.g. sensitivity, specificity, diagnostic odds ratio) and assessing their impact on task efficiency and patient health outcomes. However, most of this research has been conducted during the model development phase in controlled, laboratory settings with limited clinical studies set in real-world environments. While this research is important to establish the technical capabilities of AI as being trustworthy for use, greater emphasis needs to be placed on understanding the driving factors behind the acceptability of AI among healthcare professionals particularly as medical institutions begin to increase their investments in medical AI technologies. This is heightened by sociotechnical issues that are unique to AI technology such as poor explainability being a barrier to user understanding and trust, and the diagnostic capabilities of AI being viewed as a looming threat that will replace users rather than being an empowering tool to support them [1,3]. Accordingly, there is much research that recognises the importance of acceptability in the successful design, implementation, and value realisation of digital healthcare interventions [11–13]. Studies have shown that healthcare interventions with poor acceptability among healthcare professionals can lead to lower user uptake, a lack of meaningful and optimal value-added engagement, improper adherence with how they should be used as intended by intervention designers, and ultimately failure to realise their intended benefits even where the underlying technology was functional without error [11–13]. Indeed, many medical AI systems show promising results in theoretical lab settings but are often unsuccessful in yielding their desired benefits when deployed in medical practice because of low acceptability from healthcare professionals [14]. This has largely been caused by poor interaction design and lack of consideration for the clinical and user context among other factors [14]. Therefore, investigating the factors underpinning AI acceptability will be vital for medical institutions to pinpoint areas of deficiency and improvement within their AI implementation strategies to better ensure its intended benefits are realised.

Despite growing international interest and investment of AI in healthcare, evident in how the value of the global medical AI market is projected to increase from $13.82 billion in 2022 to $164.1 billion in 2029, research around AI acceptability in healthcare is limited [15]. The literature in this domain is sparse and fragmented which risks undermining efforts to make sense of AI acceptability. Recent reviews have been conducted that examine the literature for user perceptions and needs of AI alongside human-centred design approaches to developing AI systems to improve adoption in healthcare settings among patients and clinicians [16,17]. However, these reviews do not specifically target medical professionals in healthcare imaging fields nor do they thoroughly assess the research methodologies used to evaluate the factors underpinning the acceptability of AI. They are therefore necessarily restricted in the insights they can provide as to why different studies have reached certain results and conclusions and how researchers might improve upon these in the future. To address this gap, this scoping review aims to survey the health informatics literature to provide a comprehensive summary of the key factors influencing the acceptability of AI among medical professionals in healthcare imaging domains and to analyse the different approaches taken to investigate them. In the context of this review, the term "healthcare professionals" includes medical professionals (e.g. radiologists, radiation oncologists) who are clinicians that perform image interpretation and allied health professionals (e.g. radiographers) who typically do not perform interpretive work but may do so in some circumstances.

2. Methodology

A literature search was conducted to extract material to answer three research questions:

RQ1. What are the different ways in which acceptability has been defined or conceptualised by past studies?

RQ2. What theoretical frameworks and methodological approaches have been used to study the acceptability of AI in medical imaging domains for medical professionals?

RQ3. What are the key factors influencing the acceptability of AI in medical imaging domains for medical professionals which have been studied?

It should be noted that there is no consensus in the literature around how acceptability should be defined [12]. Four key formulations have emerged including user affective attitude towards the suitability of a system for medical usage, behavioural intention to use a system, actual system usage behaviour, and satisfaction following system usage [12]. Accordingly, acceptability in this context is not concerned with a technical perspective of the diagnostic accuracy of AI but rather the end user perspective of using AI. Restricting the ambit of this review to one specific interpretation may yield limited results given the scarcity of research in this domain. To ensure there is adequate material for analysis this scoping review will consider studies which use any of these conceptualisations of acceptability. Despite being distinctive, they all share some conceptual commonalities and therefore the insights derived from studies using different definitions of acceptability can still be informative [12].

2.1. Search strategy

An extensive search strategy was formulated in consultation with a research librarian for five academic databases including Medline, Cochrane Library, Web of Science, Compendex, and Scopus (see Supplementary File A for the search string used). The search period covered publications from January 1, 2013 to September 15, 2023. The search strategy employed subject terms where they were available and free-text terms to address the following concepts of the scoping review:

(1) **Population:** Healthcare professionals specialising in medical imaging domains particularly radiology;
(2) **Intervention:** Medical AI technology used by healthcare professionals in a medical imaging field particularly radiology;
(3) **Outcome:** Healthcare professional acceptability of AI technology denoted by the term acceptability and closely related terms including user experience, user evaluation, implementation, integration, acceptance, satisfaction, and usability.

Given the paucity of research around the acceptability of AI among healthcare professionals, the search strategy encompassed any medical imaging domain as restricting the scope to one focus area would likely yield limited results. An emphasis was placed on the radiology discipline given its leading position in AI implementation which naturally has resulted in there being more research concerning AI in radiology compared to other diagnostic imaging fields [1]. Additional articles were selected by perusing the reference lists of relevant articles. Google Scholar was further used to identify grey literature which cited pertinent studies. The search strategy only concerns material published since 2013 as this captures the time period in which AI in the healthcare imaging industry has reached a reasonable level of technical maturity for real-world deployment and as AI technology prior to this time frame will likely be significantly different in nature (e.g. user interfaces, technical performance) [1]. The search strategy process and outcome is depicted in Fig. 1.

2.2. Criteria for inclusion and exclusion

Publications were limited to journal articles, conference proceedings, and dissertations in English. Studies were only included if they were a primary study reporting on the acceptability of AI among medical professionals in healthcare imaging domains and the factors influencing it. Those which investigated acceptability at the broader organisational level or using a multi-stakeholder approach were included as long as they explicitly accounted for the end user perspective. No restriction was placed on the temporality of the study design being prospective or retrospective (i.e. before or after healthcare professional use of AI). Articles were not considered for analysis in the scoping review if they met any of the following exclusion criteria: 1) lack of any quantitative or qualitative method of data collection such as survey instruments, interviews, and focus groups; 2) the study population did not include any healthcare professionals specialising in a medical imaging domain; 3) measurement of perceptions, attitudes, and experiences of AI were not explicitly linked to the issue of acceptability; 4) the article was about

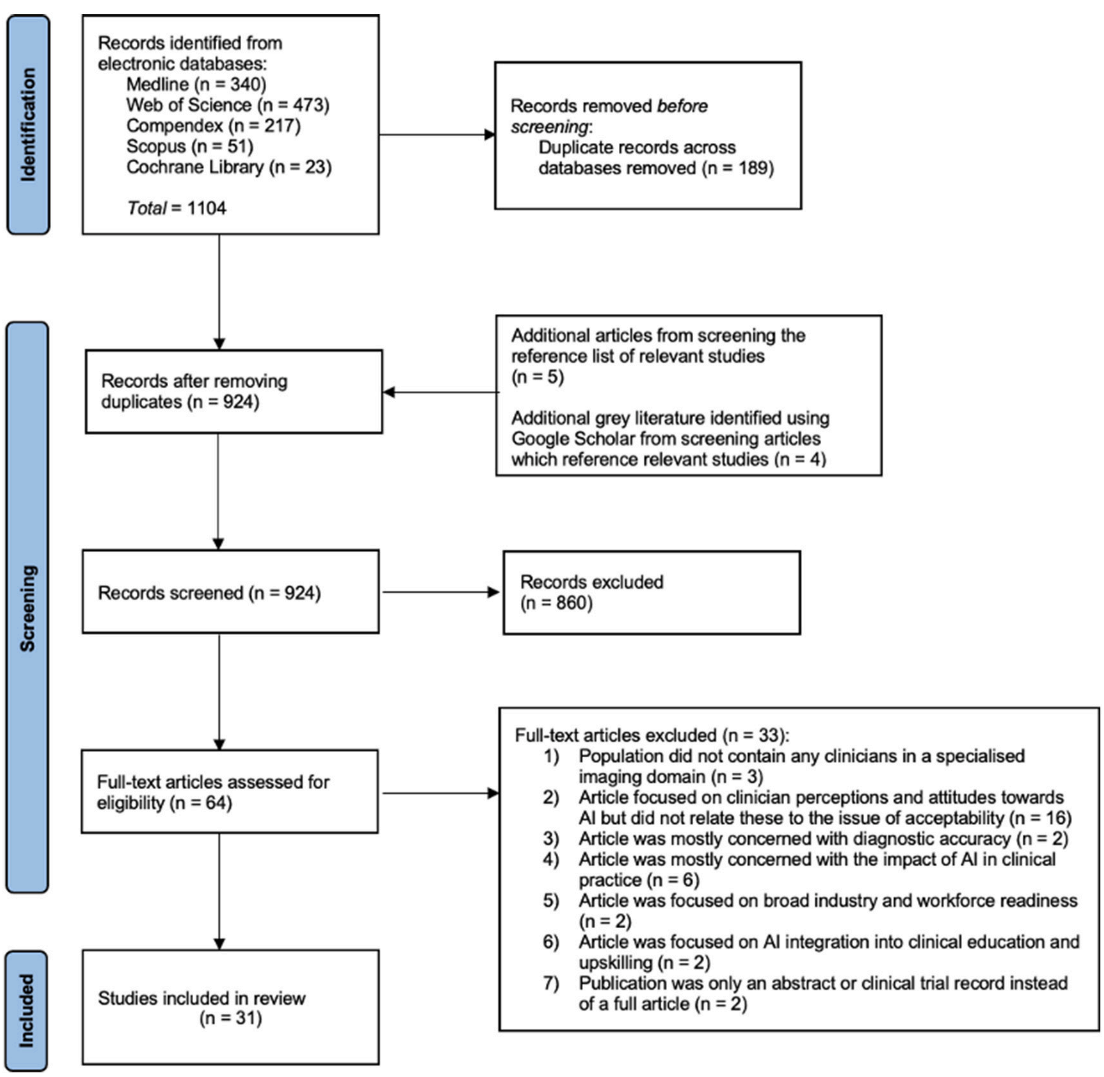

Fig. 1. Study screening and selection flow chart.

broad industry and workforce readiness; 5) the article was about AI integration into clinical education and upskilling rather than medical practice; 6) the article was predominantly or exclusively about acceptability from the perspective of the diagnostic accuracy and clinical impact of AI; and 7) the article was a review or protocol paper.

2.3. Data screening and extraction

The data screening and extraction process was completed in adherence to the PRISMA-ScR guidelines [18]. This was facilitated using the software programs of Microsoft Excel and EndNote 20. The criteria outlined above was used to screen studies firstly by title and abstract, and secondly by full-text assessment to determine whether they would be included in the scoping review. Qualitative data was collected to investigate the methodological approach adopted by each study to conceptualise and measure AI acceptance among healthcare professionals. Standardised data points were extracted from the final selection of articles including the article details (authors and their disciplinary affiliation, journal title and type, publication year) and research context (research aim and domain, type of AI system studied, setting, methodology, population, theoretical framework(s) used) which is summarised in Table 1. Thematic analysis was conducted on this collected data to answer the research questions, identify knowledge gaps in the literature, and extract emerging patterns and anomalies in the methodologies and results of the studies (e.g. how acceptability is measured by different constructs and indicators, how findings are affected by the underlying assumptions of different theoretical frameworks).

The search strategy yielded 924 articles after eliminating 189 duplicate results across the five databases. During the initial screening stage, a further five articles were included after searching the reference lists of relevant articles and an additional four grey literature publications were added after using Google Scholar to identify material citing pertinent articles. 64 out of 924 potentially relevant articles qualified for full-text assessment with 33 of these being removed under the exclusion criteria. A second researcher screened 15% of the articles by title and abstract, establishing an inter-rater reliability of 93% (125/135 agreement). Disagreements in the screening process were resolved based on discussion between the two researchers and the input of a third researcher where consensus could not be reached. Overall, the scoping review had 31 articles which were all analysed by one researcher because of resource and time constraints.

3. Results

3.1. Article characteristics

The literature search yielded 31 publications from 25 unique academic journals, two conference proceedings, and one university repository. All studies were published within the last four years (2020 to 2023 inclusive). The studies were conducted in 18 different countries, with two studies being international in scope by including multiple countries.

There is diversity in the type of journals and the backgrounds of the lead authors which can be indicative of the approach taken to investigate AI acceptability. 18 studies were published in medical journals with the majority of the lead authors having a clinical background [19–26,28–37]. This suggests a more clinically-oriented approach although Strohm et al. was the exception as Strohm's background is in innovation science which possibly reflects a more business-centric perspective [36]. Five studies were published in an information systems and management context (journal, conference, or university repository) with all first authors having this background, likely signifying a more engineering-centric approach [38–42]. Eight studies were published in interdisciplinary journals which may indicate a more holistic approach drawing from clinical and engineering perspectives [43–50]. The leader author in these papers either had an information systems or medical background but tended to collaborate with people from different disciplines.

3.2. Research aim and design

All the studies investigated AI acceptability in some capacity although their specific research aim and design varied. 24 studies sought to examine the willingness of healthcare professionals to accept the adoption of AI into medical practice and how this related to their broader perceptions, expectations, or understanding of AI; some were especially focused on exploring the nature of the facilitating and enabling factors underpinning AI acceptability while others adopted a broader institutional perspective to examine how acceptability begins at the individual level and diffuses throughout a medical organisation [19–22,24–26,28–34,36,37,39,41–43,45–48]. Four studies were empirically validating a measurement model for predicting the acceptability of AI among healthcare professionals based on established theoretical frameworks [23,38,40,50]. Three studies were a workflow-centric evaluation study seeking to investigate how healthcare professionals interact with, accept, and are affected by an AI system either in a simulated environment or real-world practice [35,44,49].

In terms of the temporality of the research design, 25 studies evaluated acceptability prospectively where participants had no opportunity to interact with a concrete AI system for the purposes of the study [19–25,28–34,37–43,45–48]. Five studies assessed acceptability retrospectively where participants had practical experience with the concrete AI system being studied [26,35,36,44,49]. Notably, only one study considered acceptability from both a prospective and retrospective perspective although this was based on whether healthcare professionals had experience with using the AI system under consideration rather than being a longitudinal study [50].

3.3. Types of AI system studied

Eight studies investigated AI acceptability in relation to an existing concrete AI system [26,35,36,39,40,44,49,50]. Six of these involved participants having practical interactions [26,35,36,44,49,50] with it while two were based on giving video demonstrations, verbal explanations, or simply informing participants of the particular system under study [39,50]. The different type of concrete AI systems studied included commercially available products (Lunit INSIGHT, BoneXpert, ATBM Master, and various diagnostic tools developed by an Israeli health technology company called Aidoc) [26,35,36,39,40], a software tool developed by a university and deployed for clinical use at a hospital [50], an application developed and validated for use at the emergency department of a health centre [49], and a prototype created for research purposes to test the usefulness of AI in medical practice [44]. The remaining 23 studies did not involve a concrete AI system which participants could interact with to form an assessment of its acceptability and instead considered AI in a general, hypothetical context. This means that these studies focused on a hypothetical AI system for use in a given healthcare context either by providing a description of the functions of a system and how it might affect medical practice, or leaving participants to their own conceptions of AI in their working environment in the absence of any such description.

3.4. Study population

The study participants encompassed healthcare professionals working in, or with, various medical imaging domains including radiology [19,20,24,29,30,34,36,40,41,45,48,49], radiography [19,21,22,33,48], dental radiography or radiology [25,31,35,43,46], radiation oncology [37,42,50], mammography [28,39,44], pathology [47], dermatology [26,32], and primary care [23]. Most studies involved clinicians and occurred in a radiological context which reaffirms how radiology is at the pioneering forefront of AI research and implementation. All studies involved practicing healthcare professionals although some had prospective healthcare professionals that were either still in medical school or undergoing placement [40,48,50]. Four studies took a multi-stakeholder approach and further considered the acceptability of AI for other types of participants who might have some influence on the perspectives that healthcare professionals hold of AI such as patients, nurses, IT staff, data scientists, medical physicists, and executive management [26,31,36,39].

3.5. Data collection methodology

The distribution of the data collection methodologies of the 31 studies included 20 quantitative studies [19–25,29,32–35,37–39,43,45,46,48,50], eight qualitative studies [26,28,30,31,36,41,42,47], and three mixed-methods studies [40,44,49]. Survey instruments were the most used data collection method overall, appearing in 23 studies (74%). As shown in Table 2, eight of these studies either directly used or extended from widely validated survey instruments, while 15 either developed their own surveys in an ad-hoc manner or adapted from an existing survey that was created in an ad-hoc fashion which had limited or no validation. The remaining data collection methods were all qualitative in nature and included semi-structured interviews [30,31,36,40–42,44,47], direct observation of user interactions with AI [44], netnography [40], and focus groups [26]. Semi-structured interviews were the most used qualitative data collection method used as they appeared in eight studies while the other qualitative methods were only used once each.

3.6. How studies have defined or conceptualised acceptability

All studies converged towards measuring a conceptualisation of acceptability which concerns the willingness or behavioural intention to adopt AI for use in daily medical practice. This notion of intended user uptake at an individual, and in some cases at the broader organisational level, was not explicitly explained by most studies. It was typically conveyed or inferred by the use of cognate terms such as “adoption”, “acceptance”, “implementation”, “integration”, and “incorporation” but surprisingly no studies used the term “acceptability”. This could be because studies treat the term “acceptability” as a linguistic variation of the term “acceptance” (i.e. the base word “accept” is retained but the suffix “ance” is replaced with “ability”) and therefore view both terms as interchangeable and expressing the same underlying concept of behavioural usage intention.

3.7. Use of theoretical frameworks

Only 14 studies employed theoretical frameworks to structure or inform their investigation of AI acceptability. Technology acceptance frameworks, which seek to explain and predict the behavioural intention of individuals to use and in turn accept an innovation, were most frequently used. This covered five studies and included extensions of UTAUT [38,40,50], TAM [49], and modified TAM 3 [39]. The second most used framework was NASSS which is designed to evaluate the successful implementation of digital healthcare technologies in a way that accounts for the individual healthcare professional, organisational systems, and wider contextual factors (reflecting micro, meso, and macro level concerns) [51]. Two studies applied NASSS with one integrating it with the technology-organisation-environment (TOE) framework to focus more on institutional readiness to adopt new technologies [36,41]. Other frameworks which were each used once included: the Diffusion of Innovations (DOI) model which seeks to explain the process behind how individuals adopt an innovation and how it subsequently permeates throughout an organisation across time [30]; the Dimension of Trust (DOT) model which focuses on how acceptability is established based on the perceived capabilities of a technological system and the degree to which users understand and view it as beneficial [52]; the Barriers and Facilitators Assessment (BFA) framework which evaluates the relevance of key factors influencing successful implementation of technologies in preventive healthcare contexts based on the characteristics of the innovation, patients, healthcare professional, and use case context [53]; the integrated Theoretical Domains Framework (TDF) and Capabilities, Opportunities, and Motivations influencing Behaviours (COM-B) model which focuses on the psychological factors governing behavioural responses and change [31]; SHAPI which examines how medical professionals perceive AI based on their preparedness for AI and beliefs about its professional impact [23]; the Consolidated Framework for Implementation Research which assess contextual factors underpinning successful implementation of innovations [26]; and the Context-Mechanism-Outcome configurations framework which captures the different combinations of aspects of interventions that work and under what circumstances [47]. The remaining 17 studies did not use a theoretical framework and instead took an ad-hoc approach by relying upon their own hypotheses and domain knowledge acquired from reviewing the literature [19–22,24,25,28,29,32–35,42,43,45,46,48].

Table 2
Survey instruments used.

Survey instrument	Studies
Extensions of the Unified Theory of Acceptance and Use of Technology (UTAUT)	[38,40,50]
Modified form of the Technology Acceptance Model 3 (TAM 3)	[39]
Dimensions of Trust (DOT)	[44]
System Usability Scale (SUS)	[44,49]
NASA Task Load Index (NASA-TLX)	[44]
Barriers and Facilitators Assessment (BFA)	[37]
Shinners Artificial Intelligence Perception Tool (SHAIP)	[23]
Ad-hoc survey	[19–22,24,25,29,32–35,43,45,46,48]

3.8. Factors influencing healthcare professional acceptability of AI in medical imaging domains

There were a diverse range of factors concerning AI acceptability in medical imaging domains which were investigated. Many of these studies overlapped by substantively measuring the same underlying concept although their wording or framing of it tended to differ. For example, the idea that AI should be perceived as successfully providing meaningful value to healthcare professionals in their work, especially when compared to their current workflow, is formulated as “perceived usefulness” by TAM 3, “performance expectancy” by UTAUT, “value proposition” by NASSS, and “relative advantage” by DOI. While these are different terms, they represent a common theme around the value proposition of AI. Overall, 12 key factors for AI acceptability were identified based on emergent themes from the studies which were measured quantitatively or qualitatively by at least two studies. These factors and their proposed definitions are outlined in Table 3.

The identified factors can further be grouped into broad, overarching categories based on commonalities in what they are measuring. These include: user factors (individual end user characteristics) involving trust, system understanding, AI literacy, technology receptiveness; system usage factors (human-computer interaction and user experience concerns) entailing value proposition, self-efficacy, burden, and workflow integration; and socio-organisational-cultural factors (contextual and environmental matters) encompassing social influence, organisational readiness, ethicality, and perceived threat. The distribution of how these conditions were examined across 31 studies is shown in Fig. 2. Value proposition was the only universally explored factor which appeared across all 31 studies. Perceived threat, AI literacy, and trust were the next most considered factors as they were evaluated 24, 19, and 18 times, respectively. Workflow integration was examined 17 times,

Table 3
Key factors underpinning healthcare professional acceptability of AI inductively extracted from past studies and their proposed definitions.

Category	Factor	Definition	Studies
System usage	Value proposition	The extent to which healthcare professionals view the use of AI as providing meaningful value to their work (e.g. improving task productivity and/or diagnostic accuracy)	[19–26,28–50]
	Burden	The perceived or experienced amount of effort required to engage with AI in daily medical practice as a reflection of the complexity it adds to the existing workflow process	[26,35,38–40,43,44,47,49,50]
	Self-efficacy	The extent to which healthcare professionals are confident in their ability to perform the necessary actions to use AI in their daily workflow (e.g. interpreting and acting upon the diagnostic recommendations of AI)	[20,26,33,35,39,44,49]
	Workflow integration	The extent to which healthcare professionals perceive the integration of AI as preserving and being compatible with their existing workflow practices	[19,20,23,25,28,31,35–37,39,40,42,44,47–50]
Socio-organisational-cultural factors	Social influence	The extent to which healthcare professionals perceive that their use of AI is expected and encouraged by influencing agents important to them (e.g. colleagues, department heads, management)	[22,30,31,36,38–40,42,50]
	Organisational readiness	The extent to which healthcare professionals believe their organisation has the necessary infrastructure, resources, or processes to facilitate the use of AI	[19–21,23,26,29,30,34,36,37,41,42,45–47,50]
	Perceived threat	The extent to which healthcare professionals perceive AI as threatening their professional role at an individual and industry level compared to being an empowering tool that enables them to be better healthcare professionals	[19–26,29–46,48,50]
	Ethicality	The extent to which healthcare professionals perceive AI as fitting with their value system (e.g. whether patient data used for AI is safely managed to protect their privacy) and that of the medical profession	[20–25,29,32,41,42,47]
User factors	Technology receptiveness	The extent to which healthcare professionals are willing to try out new innovations as part of their professional role	[21,26,31,32,35,37,38,45,48]
	AI literacy	The level of understanding and knowledge which healthcare professionals have concerning AI in general as reflected by their education, training, and experience with it	[19,20,22,23,25,29–34,36–45,48–50]
	System understanding	The extent to which healthcare professionals understand the specific AI system they are using with particular focus on how it produces diagnostic outputs alongside the purpose and role of its features in relation to their workflow	[26,30,31,35,37,38,41,44,48,50]
	Trust	The extent to which healthcare professionals believe AI is safe and dependable for use based on their level of confidence in its functional characteristics (e.g. ability to consistently provide safe and accurate diagnostic recommendations) outweighing the perceived risks of its use (e.g. incorrect and misleading recommendations)	[22,25,26,28–34,36,38,40,42,44,47,48,50]

organisational readiness 16 times, and ethicality 11 times. System understanding and burden were measured 10 times while technology receptiveness and social influence were considered 9 times. Finally, self-efficacy was only examined 7 times. It should be stressed that the frequency of any given condition is not necessarily reflective of its causal significance to acceptability.

4. Discussion

4.1. Overview of results

This scoping review has outlined the key studied factors influencing healthcare professional acceptability of AI and the varying approaches that have been employed to investigate them. Despite significant interest in the healthcare applications of AI, research around AI acceptability has been somewhat limited as only 31 studies were included in the scoping review. The lack of relevant papers prior to 2020 may reflect the slow diffusion of AI in diagnostic imaging fields which historically has been caused by scepticism towards its clinical utility, limited evidence of its diagnostic accuracy, and the lack of robust regulatory regimes [54]. The sudden recent increase in papers however suggests interest in AI usage within the healthcare imaging industry is swiftly gaining momentum as the level of technical performance becomes increasingly suitable for medical use, as the market and regulatory landscape gradually consolidates, and as evidence for the applications and benefits of AI become more convincing [54]. The broad representation of countries from North and South America, Europe, the Middle-East, Asia, and Africa reflects global interest in the use of AI for healthcare imaging domains with a slim majority of studies being concentrated in the Global North (53%). Notably, these studies were all published within the last four years which strongly indicates a growing realisation of the importance of researching AI acceptability to properly realise the benefits of AI implementation in healthcare. Although conclusive judgements cannot be drawn given the highly diverse characteristics of these studies, there are clear patterns and trends which can be observed.

4.2. Commentary on studied factors underpinning AI acceptability

The identified factors, representing emergent themes from past research, provide an extensive image of what AI acceptability entails and can help researchers to avoid a limited perspective associated with ad-hoc approaches or exclusively using one theoretical framework to inform their study design. The overarching categories into which these factors are organised reflect how AI acceptability is contingent upon a dynamic interplay of factors associated with the end user, the experience of interacting with an AI system, and the broader context in which AI is deployed. These should be kept in mind by medical organisations to ensure a more comprehensive, systematic approach to examining the strengths and deficiencies of their AI implementation strategy in relation to acceptability among healthcare professionals. This will be useful to minimising the risk of important considerations being overlooked and ensuring that the key components of AI acceptability are adequately addressed.

The parsimoniousness of the identified factors could be improved by merging factors which have a sufficient level of conceptual overlap. For example, AI literacy and system understanding share considerable overlap as they are concerned with what AI is and how it works. The point of difference – that AI literacy is about knowledge of AI generally while system understanding is about concrete knowledge of the specific system in the deployed context and appreciating its role and function in the medical workflow – may be considered as insufficient to warrant keeping them as separate factors. Conversely, some factors could be partitioned into multiple factors if there was sufficient nuance distinguishing them despite having some overlap. For example,

Table 1
Characteristics of the studies included in the scoping review.

Year	Authors and disciplinary affiliation	Journal title and type	Research aim and domain	AI system studied	Setting	Methodology	Population	Theoretical framework
2023	Agrawal et al. [20] (Clinical background)	Emergency Radiology (Medical journal)	Investigate the perceptions and expectations of clinicians towards AI implementation (emergency radiology)	No reference made to a concrete AI system. About AI in a general, hypothetical context	United States	Cross-sectional quantitative study using a survey instrument (prospective)	Radiologists from members of the American Society Of Emergency Radiology (n = 113)	No theoretical framework used
2023	Hamd et al. [46] (Clinical background)	Heliyon (Interdisciplinary journal)	Assess the knowledge, perceptions, and readiness of clinicians for AI implementation (dentistry)	No reference made to a concrete AI system. About AI in a general, hypothetical context	United Arab Emirates	Cross-sectional quantitative study using a survey instrument (prospective)	Dentists practicing in hospitals and universities (n = 134)	No theoretical framework used
2023	King et al. [47] (Clinical background)	Journal of the Medical Informatics Association (Interdisciplinary journal)	Analyse the contextual factors that support or hinder uptake of AI among clinicians (pathology)	No reference made to a concrete AI system. About AI in a general, hypothetical context	United Kingdom	Qualitative study using semi-structured interviews (prospective)	Pathologists and pathology trainees from the National Health Service (n = 25)	The Context-Mechanism-Outcome framework
2023	Verma et al. [42] (Information systems and management background)	Conference on Human Factors in Computing Systems (Information systems and management conference)	Investigate the factors affecting AI adoption in clinical settings and the desired attributes of AI needed to improve uptake (oncology)	No reference made to a concrete AI system. About AI in a general, hypothetical context	Switzerland	Qualitative study using semi-structured interviews (prospective)	Oncology practitioners from the Lausanne University Hospital (n = 7)	No theoretical framework used
2023	Catalina et al. [23] (Clinical background)	Digital Health (Medical journal)	Assess the perception of healthcare professionals towards AI, the need for AI implementation, and the impact of AI on radiology (primary care with some overlap of a medical imaging context)	No reference made to a concrete AI system. About AI in a general, hypothetical context	Spain	Cross-sectional quantitative study using a survey instrument (prospective)	Primary care medical and nursing professionals from the Catalan Institute of Health which has numerous image diagnostic centres (n = 301)	Shinners AI Perception Tool
2023	Edzie et al. [45] (Clinical background)	Heliyon (Interdisciplinary journal)	Evaluate the perspectives of clinicians towards AI and their willingness to accept it (radiology)	No reference made to a concrete AI system. About AI in a general, hypothetical context	Ghana	Cross-sectional quantitative study using a survey instrument (prospective)	Radiologists (n = 77)	No theoretical framework used
2023	Haugsten et al. [26] (Clinical background)	JMIR Dermatology (Medical journal)	Evaluate the use and implementation of an AI system to understand barriers to their adoption (dermatology)	“ATBM Master” which can detect changes in moles and estimate their probability of malignancy	Denmark	Qualitative study using semi-structured interviews (retrospective)	Doctors and nurses with dermatological work experience (n = 14)	Consolidated Framework for Implementation Research
2022	Aldhafeeri [38] (Clinical background)	Insights into Imaging (Medical journal)	Examines clinician views on the medical application of AI to better understand successful system integration (radiography)	No reference made to a concrete AI system. About AI in a general, hypothetical context	Saudi Arabia	Cross-sectional quantitative study using a survey instrument (prospective)	Radiographers from public, private, and university medical hospitals (n = 562)	No theoretical framework used
2022	Rainey et al. [33] (Clinical background)	Radiography (Medical journal)	Investigate perceptions of clinicians about AI to better understand how trust and acceptance can be	No reference made to a concrete AI system. About AI in a general, hypothetical context	United Kingdom	Cross-sectional quantitative study using a survey instrument (prospective)	Reporting radiographers (n = 86)	No theoretical framework used

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Table 1 (*continued*)

Year	Authors and disciplinary affiliation	Journal title and type	Research aim and domain	AI system studied	Setting	Methodology	Population	Theoretical framework
			improved (radiography)					
2022	Rabinovich et al. [49] (Information system and management background)	Studies in Health Technology and Informatics (Interdisciplinary journal)	Evaluate user acceptance and satisfaction of clinicians towards an AI system (radiology)	AI system developed at a health centre called "TRx" that performs automated detection of diseases in chest X-rays in an emergency department setting	Argentina	Mixed-methods study using survey instruments and semi-structured interviews (retrospective)	Radiology residents and emergency physicians at the radiology and emergency department of a university hospital (n = 13 for surveys, n = 6 for interviews)	TAM
2022	Hendrix et al. [28] (Clinical background)	Journal of the American College of Radiology (Medical journal)	To assess how different attributes of AI systems affect clinician intention to use them (mammography)	Hypothetical AI decision support tools for breast cancer detection and future breast cancer risk prediction	United States	Qualitative study using focus group interviews (prospective)	Radiologists specialising in mammography (n = 66)	No theoretical framework used
2022	Eschert et al. [25] (Clinical background)	Medicinia (Medical journal)	Assess clinician knowledge and perceptions of AI to better understand their acceptance of it (dental radiology)	No reference made to a concrete AI system. About AI in a general, hypothetical context	Germany	Cross-sectional quantitative study using a survey instrument (prospective)	Dentists with membership in the Dental Association of Westfalen-Lippe, Germany (n = 302)	No theoretical framework used
2022	Shiang et al. [35] (Clinical background)	Clinical Imaging (Medical journal)	Evaluate the real-time experiences and perceptions of clinicians towards using AI and how this impacts attitudes towards system use (radiology)	AI systems developed by Aidoc (an Israeli health technology company) for CT detection of pulmonary embolism, intracranial haemorrhage, and acute cervical spine fractures	United States	Cross-sectional quantitative study using a survey instrument (retrospective)	Radiology residents (n = 15)	No theoretical framework used
2022	Alamoudi [43] (Clinical background)	International Journal of Advanced and Applied Sciences (Interdisciplinary journal)	Assessment of clinician acceptance and willingness to use AI (radiology)	No reference made to a concrete AI system. About AI in a general, hypothetical context	Saudi Arabia	Cross-sectional quantitative study using a survey instrument (prospective)	Radiology residents and faculty radiologists (n = 55)	No theoretical framework used
2022	Pangti et al. [32] (Clinical background)	Indian Journal of Dermatology, Venerology, and Leprology (Medical journal)	Investigation into the acceptability of AI among clinicians and their attitudes and apprehensions towards it (dermatology)	No reference made to a concrete AI system. About hypothetical imaging-based AI	India	Cross-sectional quantitative study using a survey instrument (prospective)	Dermatologists and dermatology trainees (n = 166)	No theoretical framework used
2022	Calisto et al. [44] (Information systems and management background)	Artificial Intelligence in Medicine (Interdisciplinary journal)	Evaluation of AI acceptance and interaction in a simulated trial environment (mammography)	Prototype AI system called "BreastScreening-AI" that performs breast cancer diagnosis and segmentation	Portugal	Mixed-methods study using survey instruments, semi-structured interviews, and quantitative data for productivity and diagnostic accuracy analysis (retrospective)	Clinicians from public hospitals, private clinics, and cancer institutes (n = 45)	Dimensions of Trust adapted from Cai et al. [52]
2022	Abuzaid et al. [19] (Clinical background)	Academic Radiology (Medical journal)	Assessment of willingness to accept AI integration (radiology, radiography)	No reference made to a concrete AI system. About AI in a general, hypothetical context	United Arab Emirates	Cross-sectional quantitative study using a descriptive survey instrument (prospective)	Radiologists and radiographers (n = 153)	No theoretical framework used

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Table 1 (*continued*)

Year	Authors and disciplinary affiliation	Journal title and type	Research aim and domain	AI system studied	Setting	Methodology	Population	Theoretical framework
2021	Botwe et al. [22] (Clinical background)	Radiography (Medical journal)	Assessment of perspectives towards AI integration and how future adoption can be supported (radiography)	No reference made to a concrete AI system. About AI in a general, hypothetical context	Africa	Cross-sectional quantitative study using an exploratory survey instrument (prospective)	Radiographers (n = 1020)	No theoretical framework used
2021	Zhai et al. [50] (Clinical background)	Journal of Medical Internet Research (Interdisciplinary journal)	Empirically test a measurement model to investigate the factors driving AI acceptance (radiation oncology)	AI tool which automates the contouring process for cancer patient scans. Developed at the Sun Yat-sen University Cancer Center and deployed for clinical use since 2019	China	Quantitative study using a survey instrument (prospective or retrospective depending on user exposure)	Medical students as prospective radiation oncologists, practicing radiation oncologists (n = 307)	UTAUT extended with additional constructs
2021	Mugabe [37] (Clinical background)	Technical Innovations and Patient Support in Radiation Oncology (Medical journal)	Investigation of the facilitators and barriers to adoption of AI (radiation oncology)	No reference made to a concrete AI system. About AI in a general, hypothetical context	New Zealand	Quantitative study using a survey instrument (prospective)	Radiation oncologists, medical physicists, and senior radiation therapists (n = 101)	BFA framework adapted from Harmsen et al. [53]
2021	Pumplun et al. [41] (Information systems and management background)	Hawaii International Conference on System Sciences 2021 (Information systems and management conference)	Exploration of the factors driving the AI adoption process and clinical readiness for AI (radiology)	No reference made to a concrete AI system. About AI in a general, hypothetical context	Germany	Qualitative study using semi-structured interviews (prospective)	Healthcare leadership staff from various imaging-based domains with most being radiologists (n = 15)	TOE framework integrated with NASSS framework
2021	Huisman et al. [29] (Clinical background)	European Radiology (Medical journal)	Investigation of clinician willingness for AI integration into medical practice and resident programs, and the hurdles to AI implementation (radiology)	No reference made to a concrete AI system. About AI in a general, hypothetical context	International, spanning 54 countries	Cross-sectional and multi-centre quantitative study using a survey instrument (prospective)	Radiologists and radiology residents (n = 1041)	No theoretical framework used
2021	Gerigoorian and Kloub [39] (Information systems and management background)	Combined Undergraduate Thesis in Computer and Information Sciences (Information systems and management thesis)	Examine the factors driving acceptance of a deployed AI system prior to use in a hospital environment (mammography)	Commercial AI computer-aided detection (CAD) system for supporting breast cancer detection called “Lunit INSIGHT MMG”	Sweden	Quantitative study using a survey instrument (prospective)	Radiologists, nurses, and IT staff working in a hospital breast screening unit in Stockholm, Capio St Göran Hospital (n = 28)	Modified version of TAM 3
2021	Qurashi et al. [48] (Clinical background)	Journal of Multidisciplinary Healthcare (Interdisciplinary journal)	Assessment of perceptions and acceptance levels towards medical AI integration (radiography)	No reference made to a concrete AI system. About AI in a general, hypothetical context	Saudi Arabia	Cross-sectional quantitative study using a survey instrument (prospective)	Radiographers, radiologists, clinical application specialists, internship radiography students (n = 224)	No theoretical framework used
2021	Morrison [30] (Clinical background)	Future Healthcare Journal (Medical journal)	Investigation of the barriers and enablers for the adoption of AI among staff in the National Health Service (radiology, pathology)	No reference made to a concrete AI system. About AI in a general, hypothetical context	United Kingdom	Qualitative study using semi-structured interviews (prospective)	Healthcare professionals from radiology, pathology, and general practice (n = 12)	DOI
2021	Müller et al. [31] (Clinical background)	Journal of Clinical Medicine (Medical journal)	Investigation of the barriers and enablers for the implementation and acceptability	No reference made to a concrete AI system. About AI in a general, hypothetical context	Germany	Qualitative study using semi-structured interviews (prospective)	Patients and dentists specialised in radiographic	TDF integrated with COM-B model

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Table 1 (*continued*)

Year	Authors and disciplinary affiliation	Journal title and type	Research aim and domain	AI system studied	Setting	Methodology	Population	Theoretical framework
			of AI (dental radiographic diagnostics)				diagnosis (n = 13)	
2021	Prakash and Das [40] (Information systems and management background)	Information and Management (Information systems and management journal)	Empirically test a measurement model to investigate the factors affecting behavioural intention to use AI (radiology)	AI system called "Lunit INSIGHT" providing diagnostic recommendations for use with chest X-rays and mammography	India	Mixed-method study using netnography, semi-structured interviews, and a survey instrument (prospective)	In-training and practicing radiologists, imaging department heads (n = 15 for interviews in Study 1, n = 183 for survey for Study 2)	Modified UTAUT integrated with status quo bias and technology trust theories
2021	Coppola et al. [24] (Clinical background)	La radiologia medica (Medical journal)	Examine clinician views towards AI implementation in practice and how this relates to adoption rates (radiology)	No reference made to a concrete AI system. About AI in a general, hypothetical context	Italy	Cross-sectional quantitative study using a survey instrument (prospective)	Radiologist members of the Italian Society of Medical and Interventional Radiology (n = 1032)	No theoretical framework used
2021	Shelmerdine et al. [34] [Clinical background]	Paediatric Radiology (Medical journal)	Evaluate the attitudes and perceptions of healthcare professionals towards AI and how this relates to willingness of use (paediatric radiology)	No reference made to a concrete AI system. About AI in a general, hypothetical context	International (United Kingdom, Australia, New Zealand, Europe, United States)	Cross-sectional quantitative study using a survey instrument (prospective)	Members of various international paediatric radiology societies (n = 240)	No theoretical framework used
2020	Strohm et al. [36] (Innovation sciences background)	European Radiology (Medical journal)	Investigate the barriers and facilitators to the implementation and acceptance of AI (radiology)	Commercial X-Ray AI software called "BoneXpert" which performs automated bone maturity assessments based on paediatric hand scans of patients	Netherlands	Qualitative study using semi-structured interviews (retrospective)	Radiologists, clinical physicists, data scientists, management staff, innovation and implementation executives (n = 24)	NASSS framework
2020	Fan et al. [38] (Information systems and management background)	Annals of Operations Research (Information systems and management journal)	Investigate the factors explaining adoption of AI (medical imaging field - unspecified)	No reference made to a concrete AI system. About AI in a general, hypothetical context	China	Quantitative study using a survey instrument (prospective)	Healthcare professionals from medical imaging and medical clinical departments (n = 191)	Modified UTAUT integrated with trust theory and additional constructs

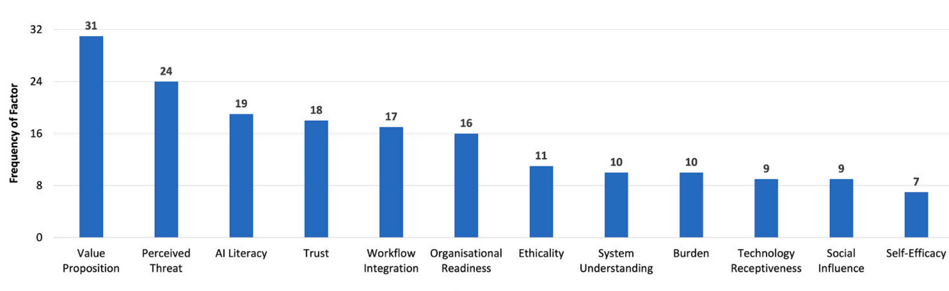

Fig. 2. Distribution of factors influencing healthcare professional acceptability of AI in the primary studies.

organisational readiness could be split into technical infrastructural readiness and organisation process readiness to address different aspects of institutional preparedness for AI. A possible approach which can address these concerns is to develop a conceptual framework designed specifically for AI acceptability which consists of unidimensional and multi-dimensional constructs. How the factors reported here are interpreted is a matter to be decided by researchers and medical organisations as the primary objective of this scoping review is to summarise what has been studied to provide a starting point for making sense of AI acceptability.

4.3. *Theoretical frameworks and ad-hoc approaches used*

Theoretical frameworks offer a structure of descriptive elements (e.g. concepts, constructs, variables) to guide research based on a formal theory or theories which provide a coherent interpretation of some phenomenon [55]. They provide a theoretical underpinning and systematic approach to research, ensuring more comprehensive coverage of the important elements of the phenomenon of interest especially when compared to ad-hoc approaches [55]. However, they can also provide a narrow, constrained perspective because of their underlying design, assumptions, and intended use cases [55]. Many of the theoretical frameworks used by previous studies, in their original form, are arguably unsuitable for examining the intricacies and nuances of AI acceptability in healthcare. This limitation stems from the frameworks lacking consideration of healthcare-specific issues, treating AI no differently to past digital health technologies, and being consumer-centric or business-centric in their perspectives.

The majority of the frameworks used do not explicitly embed contextual healthcare and human factors which are crucial to AI being used as a healthcare intervention. Without further modification, they fail to account for critical concerns in a medical context such as the implications of AI on human life and patient safety, the qualitative and empathetic components of medical practice, organisational and professional culture, how integration into workflow processes and human-machine interactions might impact the medical decision-making process, the norms of healthcare professions especially around safety and risk, and trust and ethics which are foundational components to medical practice [56]. Only a minority of frameworks are specifically designed to consider technology in a healthcare context including NASSS, BFA, and the integrated TDF and COM-B framework, and the SHAIP.

All but one of the frameworks used are technology-agnostic and therefore treat AI the same as any other technology. This means they overlook the unique technical properties and challenges of AI (e.g. dynamic learning, extrapolating from the past to make predictions about the future, algorithmic bias) which distinguishes it from past technologies which are static and more simplistic in their behaviour. They further cannot capture nuanced sociotechnical issues that are specific to AI such as: issues of system transparency which can inhibit trust from being unable to critically interrogate the reasoning behind an output; the perceived threat of AI to professional autonomy based on fears about deskilling, replacement or redundancy, and overreliance grounded in the near-human performance of AI systems which can operate continuously at scale; and how AI literacy may affect the user interaction experience as effective AI usage arguably requires knowledge and skills that are qualitatively different from those associated with digital literacy to use general information technologies [3,17,40]. These frameworks also do not account for the status of AI as SaMD which is associated with the clinical ramifications it can have on patient health and management outcomes. This is because AI in medical imaging contexts primarily serves a medical function and naturally has more complex considerations such as medico-legal issues and requiring regulatory approval by governmental bodies. This is unlike other many digital healthcare technologies (e.g. electronic health records, telehealth) which are used to automate manual tasks or digitise workflow processes. Moreover, most of the theoretical frameworks were originally designed to study the behaviour of lay consumer and business end users where productivity and usability are the predominant concern. They do not account for healthcare professionals being the target audience who have specialist expertise and different priorities which inform their perspective on acceptability [57]. For example, studies have found that healthcare professionals tend to be more pragmatic by placing greater emphasis on factors which are important to improving outcomes and upholding patient safety (e.g. value proposition, trust, ethicality) while giving lesser weighting to factors which are not as crucial to achieving this objective (e.g. system burden, social influence) [57].

Studies using theoretical frameworks often made extensive modifications to account for these limitations, indicating that existing tools in their original state are ill-equipped to address the complexities of this domain. This does not necessarily mean that these frameworks have no value and should be avoided when investigating AI acceptability in healthcare. Although developing new frameworks is a possible option, these frameworks can still provide useful and relevant insights if they are extended to better reflect the realities of how healthcare professionals perceive and interact with AI in real-world medical settings as discussed above. Meanwhile, studies which did not use any theoretical frameworks tended to be less systematic and comprehensive in their coverage of the factors that might influence healthcare professional acceptability of AI. The use of an ad-hoc approach resulted in some studies overlooking factors that were embedded in the theoretical frameworks used (e.g. organisational readiness, social influence, burden). Yet, this approach often afforded them the flexibility to target more novel and specific aspects of AI in healthcare (e.g. workflow integration, AI literacy, ethicality) that are not embedded in the perspectives of some of these theoretical frameworks. Notably, the SHAIP was the only framework which is explicitly designed to address the use of AI in healthcare by medical professionals and captures a meaningful subset of the key factors observed in this review. However, it still overlooks some noteworthy factors (e.g. workflow integration, trust, AI literacy) which may be attributed to it only containing 10 questions [23].

4.4. The need for conceptual clarity and terminology consistency

There is a need for conceptual clarity concerning how acceptability is defined and terminology uniformity for how different terms considered synonymous or interchangeable with it are used. Rather than relying on the ordinary definition of words, studies should be explicitly clear in what they conceptually mean when they use the word “acceptability” or terminology associated with it (e.g. “adoption”, “acceptance”, “implementation”, “integration”, “incorporation”). This is important to distinguish acceptability from closely related but distinct concepts (e.g. usability, feasibility, enjoyment) which can often be conflated with acceptability [13,58]. This is particularly the case where researchers adopt a novel interpretation of acceptability based on the context of their study although all the studies in this review adopted the same conceptualisation of acceptability. Otherwise, this creates unnecessary confusion around how acceptability is being used which makes it more difficult to understand and compare the results of different studies. More uniform and clearer usage of terminology by the research community will be key to facilitating a more cohesive and consistent investigation into AI acceptability [12].

4.5. Accounting for study temporality when interpreting observations of AI acceptability

The temporality of each study (prospective or retrospective) is an important methodological factor that must be considered when interpreting the reported results on the acceptability of AI among medical professionals for each study. In prospective studies, where participants do not have the chance to practically engage with an AI system, it is possible that healthcare professionals could have a distorted perspective of AI (which could either be favourable or unfavourable) based on preconceived notions or speculative views around the value proposition of AI and how it would concretely operate in their specific clinical workflow context. In retrospective studies, where participants have interacted with a concrete AI system, the reported acceptability of AI will be grounded by the experiences of healthcare professionals using it and a contextualised understanding of how AI actually works in real-world or simulated medical practice. Therefore, the significance attributed to different factors and the outcome of AI acceptability among participants could be affected by the study temporality in a non-trivial manner. Differences in whether a study population was practically exposed to an AI system could indeed be a consequential or decisive factor in determining if AI is ultimately deemed acceptable. Future systematic reviews and meta-analyses on this topic should ensure to conduct a sub-group analysis based on temporality to better understand how AI acceptability outcomes might vary based on study temporality.

4.6. Gaps in existing research

There is some research that investigates the relationship between AI literacy and AI acceptability among healthcare professionals although there is limited work examining the interventional impact that different types of AI educational programs (e.g. self-learning, structured courses, work seminars and training) can have on improving acceptability. Studies have empirically shown that lower digital literacy is associated with more negative attitudes towards innovations in healthcare settings but that improving it can increase acceptability [59]. Validating whether this extends to AI in healthcare settings for AI literacy would be useful in informing the priority that medical organisations give to training and educating staff around AI and how precisely it should be delivered. Moreover, there is limited work examining the nature of human-AI interactions and the implications this can have on acceptability and desired outcomes. Calisto et al. was the only study to examine how system usability facilitated by human-centred design principles impacted diagnostic accuracy, productivity, and acceptability [44]. They found that the use of an AI system with high levels of acceptability on average contributed to reducing diagnosis time by three minutes, false positives by 27%, and false negatives by 4% [44]. This raises questions about the minimum level of expected improvement in outcomes needed to conclude with statistical significance the benefits of AI usage and the extent to which this can be attributed to acceptability.

In general, there is limited research which examines AI acceptability retrospectively with reference to a concrete AI system in a real-world rather than simulated setting. The scope of what can be examined is necessarily limited if considering AI prospectively in hypothetical terms (e.g. the user experience and how AI integrates into the medical workflow can only be examined meaningfully if a tangible AI system is involved) or if examining AI retrospectively in a simulated environment (e.g. organisational and cultural factors which impact how the workflow is approached is difficult to replicate in a controlled setting). It would also be worthwhile to examine AI acceptability through the lens of other formulations of acceptability. Other notable research gaps which warrant further investigation because of their implications on acceptability include: the use of explainable AI systems, perceptions of technical maturity compared to actual performance, the nature of the medical workflow and the specific deployment context, and user awareness of industry trends and the position of professional medical bodies and societies concerning AI.

4.7. Limitations

There are some limitations with this scoping review. The primary limitation concerns how the search strategy was formulated with respect to the intervention context. This review focused on the perspective of radiologists as they are most likely to be exposed to AI compared to other healthcare imaging domains given that significant AI research and development has been directed towards diagnostic radiological problems that require complex analysis of medical images. Although the search strategy was designed to include any medical imaging field, the search terms employed did not explicitly address other imaging contexts (e.g. radiography, radiation oncology, mammography) and attempted to capture all of them using the "imaging" free-text term and "Diagnostic Imaging" search term. In particular, radiography was excluded as a search term since the responsibilities of radiographers primarily involve capturing medical images rather than interpreting them and hence they were not a priority for this review despite their significant role in radiological systems. Nevertheless, this approach could have potentially caused some pertinent studies to be excluded if they were not associated with these terms in the electronic databases searched. Furthermore, only one researcher conducted the full screening process and qualitative analysis of the final set of 31 papers which could introduce some bias into the results. To help safeguard against this, another researcher screened a subset of all the papers including the final set of studies. Additionally, this review narrowly focuses on AI acceptability from the perspective of healthcare professionals and by design excludes the views of other important stakeholders (e.g. patients, nurses, hospital support staff) in healthcare imaging contexts. Finally, this research does not critically analyse the reported importance of different factors to AI acceptability for each study although this is an exercise in evidence synthesis that is more suited to a systematic review and meta-analysis.

4.8. Future work and direction

Further inquiry into AI in medical imaging domains should be pursued given the limited number of studies that exist. This will be useful from both a theoretical and practical perspective to develop a corpus of knowledge around how AI acceptability can best be achieved across varying imaging sectors to provide different medical organisations with more concrete and relevant insights to their circumstances. This will be valuable in facilitating the integration of AI into existing healthcare systems and workflows. This will require deeper consideration of questions which have been overlooked by the literature such as: What is the impact of AI on the medical workflow and operational practices? What are the different ways to approach human-AI collaboration to ensure effective co-existence and optimal augmentation of medical practice? What is the interventional impact of AI literacy on user acceptability?

A more robust study design for future research in this domain is warranted through utilising a mixed-methods approach rather than exclusively applying a qualitative or quantitative methodology which was what most studies used. The majority of studies exclusively used either semi-structured interviews (as part of a small-N qualitative study) or survey instruments (as part of a medium-N to large-N quantitative study) for data collection concerning AI acceptability. The subjective, self-reported nature of the data collected using these methods is highly susceptible to, and often skewed by, participant bias [60,61]. To improve result validity and reliability, it should be triangulated with observational data (e.g. participation observation, user experience and usability testing) alongside technical system data (e.g. task performance, keystroke and mouse click activity) to produce a more complete, objective image of acceptability. Where possible, researchers should endeavour to establish the user context and understand the nature of the concrete AI-assisted workflow for the participants being studied to better contextualise and inform their investigation of AI acceptability. This is absent from most studies and can lead to incorrect assumptions or interpretations concerning user perceptions of AI, and hinder a more nuanced analysis of results.

Studies which were empirically validating a measurement model tended to treat the factors underpinning AI acceptability as being causally independent and therefore focused on assessing the net impact of individual factors on acceptability in isolation from other factors [23,38,40,50]. This may limit the insights produced given that acceptability is likely a causally complex behavioural phenomenon driven by factors that are dynamically interacting with each other. Applying configurational approaches may be necessary to provide a combinatorial perspective of how different factors work together to holistically produce the outcome of AI acceptability. This will be beneficial to untangling the complexity underpinning different end user experiences of AI which each have different causally intertwined factors at play.

It can be expected that research in this domain will continue to expand as AI becomes increasingly used by healthcare professionals. However, future work must not neglect to investigate AI acceptability for patients in light of the growing uptake of AI-powered consumer digital health interventions (e.g. mental health chatbots, remote patient monitoring, smart health trackers). The nature of acceptability could plausibly vary between those that receive (patients) and administer (healthcare professionals) medical AI technologies because of differences in needs, preferences, and the context of the system use case [11,12]. The perspectives of medical practitioners will be significantly shaped by their specialist expertise and professional norms, whereas the view of patients will tend to be affected more by social approval based on the recommendations of other consumers and healthcare professionals [11,12].

It would be worthwhile to perform an updated review in the coming years to see whether new factors influencing AI acceptability emerge and how methodological approaches for investigating acceptability have evolved as AI becomes increasingly integrated into medical systems. A systematic review accompanied by a meta-analysis would be particularly valuable to compile evidence for the causal impact, relative significance, and interrelationships of these factors to achieving high levels of healthcare professional acceptability of AI.

5. Conclusion

This is the first scoping review to survey the health informatics literature around the key factors influencing the acceptability of AI among healthcare professionals in medical imaging contexts and the methodological approaches adopted by past research to investigate it. It highlights the complex multiplicity of factors at the user, system usage, and socio-organisational-cultural level that need to be considered to properly address the nuances of AI acceptability in healthcare. This demonstrates how the acceptability of AI as a digital healthcare intervention is distinctive from the acceptability of other technologies which typically are targeted towards lay consumer or business end users and do not have significant implications on human welfare. To ensure a more comprehensive investigation of AI acceptability, future studies should ensure to address a meaningful combination of the key factors identified by this scoping review. As investment and research into AI for healthcare increases, it would be valuable to conduct a systematic review accompanied by a meta-analysis in the future to synthesise the empirical evidence around the contribution of these factors to achieving high levels of healthcare professional acceptability of AI.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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