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Review Article

Artificial Intelligence user interface preferences in radiology: A scoping review

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ABSTRACT

Introduction/Background: Modern forms of Artificial intelligence (AI) have developed in radiology over the past few years. With the current workforce shortages, in both radiology and radiography professions, AI continues to prove its place in supporting clinical radiology processes. The aim of the scoping review was to investigate the existing literature on the topic of preference of use of artificial intelligence interfaces within a radiology context.

Methods: Using a systematic approach, papers were chosen against an inclusion criterion of addressing radiological AI user interface preferences to be included in the scoping review. Arksey O'Malley's and Levac's framework were used to inform the procedural steps for the scoping review. Four databases were searched including MEDLINE Ovid, Scopus, Web of Science and Engineering Village. Reliability was improved through the involvement of three researchers to select the papers against the inclusion criteria.

Results: Six papers were identified to fit the inclusion criteria of radiological AI user interface preferences. These varied methodologically including two observational studies, two simulated user testing studies, a diagnostic accuracy study and a multi-case study. AI user interfaces were evaluated in two studies. Mixed responses were obtained with some alignment in preference for heatmap image overlays and highly detailed user interfaces are linked to higher preference amongst users. Limited literature exists on AI user interfaces and a lack of research evaluating current AI interface preference, either in post or pre-deployment.

Discussion: The mix of methods used within studies indicated that there is not yet a standardised method for assessing AI tool design and preference within radiology, with common use of a System Usability Scale survey tool in conjunction with another method. There was also a varied response when considering the preferred user interface in radiology, though simple, non-complicated designs were suggested to be ideal by participants.

Conclusion: Medical imaging AI user interface research is essential for the acceptability of AI technology into radiology departments. This scoping review identified the current landscape of AI user interface research within a radiology setting. There is a requirement for more radiology AI research focussing on end user or imaging professional involvement and their preferences. There is an explicit need for further research in the field, due to the lack of standardised outcome measures, lack clear findings regarding ideal user interfaces and lack of inclusion of radiographers. The dearth of studies including radiographers and small sample sizes of participants within these studies identifies the mindset shift required for radiology, and AI vendors alike.

RÉSUMÉ

Introduction/Contexte: Des formes modernes d'intelligence artificielle (IA) se sont développées en radiologie au cours des dernières années. Compte tenu de la pénurie actuelle de main-d'œuvre, tant en radiologie qu'en radiographie, l'intelligence artificielle continue de prouver qu'elle a sa place dans les processus de radiologie clinique. L'objectif de cette étude était d'examiner la littérature existante sur le thème de la préférence d'utilisation des interfaces d'intelligence artificielle dans le contexte de la radiologie.

Méthodologie: En utilisant une approche systématique, les auteurs ont sélectionné les articles en fonction d'un critère d'inclusion por-

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tant sur les préférences d'utilisation des interfaces d'intelligence artificielle en radiologie, afin de les inclure dans l'étude exploratoire. Le cadre d'Arksey O'Malley et de Levac a été utilisé pour informer les étapes de la procédure de l'examen exploratoire. Quatre bases de données ont été consultées : MEDLINE Ovid, Scopus, Web of Science et Engineering Village. La fiabilité a été améliorée par la participation de trois chercheurs à la sélection des articles en fonction des critères d'inclusion.

Résultats: Six articles répondant aux critères d'inclusion des préférences en matière d'interface utilisateur de l'IA radiologique ont été identifiés. Les méthodes varient : deux études d'observation, deux études de simulation d'essais par l'utilisateur, une étude sur la précision du diagnostic et une étude multi-cas. Les interfaces utilisateur de l'IA ont été évaluées dans deux études. Des réponses mitigées ont été obtenues, avec un certain alignement dans la préférence pour les superpositions d'images de cartes thermiques, et les interfaces utilisateur très détaillées sont liées à une préférence plus élevée parmi les utilisateurs. La littérature sur les interfaces utilisateur de l'IA est limitée et il n'existe pas de recherche évaluant les préférences actuelles en matière d'interface de l'IA, que ce soit en post-déploiement ou en prédéploiement.

Discussion: Le nombre de méthodes utilisées dans les études indique qu'il n'existe pas encore de méthode standardisée pour évaluer la conception et la préférence des outils d'IA en radiologie, avec l'utilisation courante d'un outil d'enquête System Usability Scale en conjonction avec une autre méthode. Les réponses ont également été variées en ce qui concerne l'interface utilisateur préférée en radiologie, bien que les participants aient suggéré que des conceptions simples et non compliquées soient idéales.

Conclusion: La recherche sur l'interface utilisateur de l'IA en imagerie médicale est essentielle pour l'acceptabilité de la technologie de l'IA dans les services de radiologie. Cet examen exploratoire a permis d'identifier le paysage actuel de la recherche sur l'interface utilisateur de l'IA dans un cadre radiologique. Il est nécessaire de mener davantage de recherches sur l'IA en radiologie, axées sur l'implication de l'utilisateur final ou du professionnel de l'imagerie et sur ses préférences. Il existe un besoin explicite de recherche supplémentaire dans ce domaine, en raison du manque de mesures de résultats standardisées, du manque de conclusions claires concernant les interfaces utilisateur idéales et de l'absence d'inclusion des radiographes. La rareté des études incluant des radiographes et la petite taille des échantillons de participants dans ces études mettent en évidence le changement d'état d'esprit nécessaire pour la radiologie et les fournisseurs d'IA.

Keywords: Artificial intelligence; Radiography; Education; Human-computer interaction

Introduction

Technology has advanced exponentially over the last two decades and continues to revolutionise the way humans live and work. This advancement has been accepted differently across generations and changes have affected all individuals differently [1]. Healthcare is a sector that has been influenced by technology and continues to demonstrate the widespread day to day impact on patients from advancements in new drugs to new equipment [2].

Modern forms of Artificial intelligence (AI) have developed in radiology over the past few years [3]. With the current workforce shortages, in both radiology and radiography professions, AI continues to prove its place in supporting clinical radiology processes [4,5]. This has been in the form of assistive reporting, image quality optimisation, examination vetting and workflow management [6].

AI has also been introduced into pre-registration healthcare education as professions move to integrate the technology for future workforces [7]. Governing bodies such as the Health and Care Professions Council (HCPC) have released documentation such as the Standards of Proficiency for Radiographers [8] to account for the introduction of AI and now requires all registrants to understand the principles of AI and applications to clinical practice. Organisations such as the National Institute for Health and Care Excellence (NICE) have also recognised the value of AI in radiology in different imaging contexts, though for some products, NICE has recommended more research to support their use in practice [9].

Despite the benefits of AI technology, it has been met with resistance from some healthcare professionals as it begins to be implemented within clinical practice in radiology. Attitudinal and opinion research on the subject has reflected this with an increase in the amount of published literature surrounding the sociological factors influencing the implementation of AI systems within radiology [10–13]. Research relating to users purports the perception that AI advice may be less diagnostically accurate than human advice [11] and that there is a lack of existing knowledge and skills surrounding usability of the technology [14,15]. There is also a generalised fear from users, of AI technological errors and lack of knowledge around the technological processes that leads AI to the clinical diagnoses, or "black box" thinking [12]. Another highly engaged issue, affecting integration within radiology, is the trustworthiness of AI technology including transparency and epistemic opacity [16]. Explainability is a fundamental part of this and ensues users to be able to explain the AI decision-making processes. This relates to users accepting AI technology, as it has been suggested to empower clinicians and subsequently patients, to promote trust and informed decision making [16]. There is a requirement for AI technology to incorporate humans into their processes to optimise the acceptance of the technology and address legal and ethical challenges [17]. Gefter et al. [18] suggested a move towards Human-AI symbiosis and encourage the notion that AI is to work alongside the radiologist, not replace them. The European Union AI Act2023 also maintains that AI technology remains dutifully transparent and trustworthy [19] A large part of this human and machine interaction involves the User Interface (UI) that clinicians use as the interface connecting them to the medical diagnosis or report. Though there is currently a lack of UI standardisation within the fields of medical imaging and AI technologies, recent research has outlined recommendations in maintaining human centric approaches when designing these, encompassing feedback from users of the product and common issues alongside factors such as clinical relevance and integration [20,21].

There are a variety of UIs available from different developers/manufacturers, such as (i) Region of Interest (ROI) indication, (ii) 'heat' or salience maps, (iii) binary models and (iv) textual reports [22,23]. There has been limited research investigating the correlation between UI, user performance and preference [23,24]. It is integral for technological advancement that human-centric interfaces are used to instil trust into the clinicians using the AI [25]. Without this, imaging professionals will be reluctant to accept AI leading to a lack of machine learning development [26], or conversely staff may decide to over-rely on the system, deskilling the workforce leading to errors [27].

This scoping review is therefore timely to investigate existing literature on user preferences for medical imaging AI-based UIs, to ensure appropriate engagement with the information provided by the technology. There is currently no scoping review related to preference in user interfaces within radiology and indicates a need for exploration. The aim of this review is to synthesise and identify the gaps in the literature, to explore current perspectives of AI UIs in radiology and radiography practice, relating to clinical radiology. Subsequently, the review question was finalised as "What is known from the existing literature about user preferences regarding artificial intelligence systems and user interfaces in a medical imaging context?".

Methods

The authors have no conflict of interest but have acknowledged that the initial author is receiving Department of Economy funding to support their PhD studies. The review followed the Arksey & O'Malley [28] methodological research framework using the five steps: identifying the research question, searching for relevant studies, selecting the studies, charting the data, summarising the results, and consulting with stakeholders to inform or validate study findings. This was in combination with the development of the Arksey & O'Malley framework suggested by Levac et al. [29] which focusses on clarification and more detail around each stage.

To be included in the scoping review, articles needed to measure or focus on the AI user interface characteristics of medical images and have an element of preference, in the study (Table 1). Relating to the PCC search elements, the "Population" was defined as Radiographers or radiologists or any other healthcare professional that would use AI technology in radiology e.g., Emergency Department clinicians. The "Concept" was defined as the evaluation of visual imaging characteristics or user interface of the AI technology and AI user interface design in radiology. The "Context" is healthcare settings.

The search strategy is demonstrated in Table 2 and Table 3. Peer reviewed journal articles were included from the timeframe of 2013–2023, in the English language and described AI user interface characteristics of medical images in relation to radiographers, radiologists, students and any other healthcare professional that would interact with the technology such as Emergency Department (ED) clinician. Qualitative, quantitative, and mixed methods studies were included to allow for the breadth of information on AI image user interface and preference. Articles were excluded if they did not relate to the investigation of AI user interfaces of medical images or had a focus on the opinions of users of AI in radiology, without the aim of exploring AI design or AI user interface and user preference. Additionally, any papers that did not mention imaging professionals e.g., radiologists or radiographers, or professionals regularly in review of medical images. Articles were tabulated as seen in Supplementary Material with the headings; *year of publication, location, participant population, methodology, sample size, outcome measures, important results, recommendations, elements of human-centred design, type of user interface and perceptions, use of AI guidelines, output of the AI, type of intervention, type of AI, auxiliary professionals mentioned and inclusion of the System Usability Scale (SUS).* These headings were synthesised schematically indicative of characteristics of all the articles included in the review.

To identify potentially relevant documents, the following bibliographic databases were searched December/January 2024: MEDLINE Ovid, Scopus, Web of Science and Engineering Village. 10 years was the time frame used due to the developments within AI in radiology over the past few years [3] and additionally an IDTechX report [30] identified the early 2010s as revolutionary for image recognition and analysis due to the introduction of deep learning techniques. MEDLINE Ovid, Scopus, Web of Science are all health-focussed databases aligning with the investigation of research into AI user interfaces in radiology. Engineering Village was included as it covers computing and engineering, which encompasses AI user interface and the human elements focussed on in this scoping review.

The search strategies were identified with help from a subject specialist librarian at the authors' academic institution. Publications were identified from the four databases and hand searching from the reference list of relevant articles, using the search criteria, though some were removed due to not meeting the inclusion criteria through review of title and abstract.

Articles were screened from their title and abstract. Papers that did not meet the search criteria were removed. The remaining papers were read in full and duplicates or irrelevant papers were removed. Citations were assessed in detail against the inclusion criteria by two independent reviewers. As a scoping review was undertaken to contribute to a comprehensive overview of existing literature [41] surrounding AI user interfaces in radiology, an exploration into risk of bias is unnecessary. However, reporting biases were considered through the process relating to two independent reviewers and an additional reviewer present for arbitration if necessary. For example, disagreements that arose between independent review-

Table 1
Database search strategy.

Database	Search terms	Articles found
MEDLINE OVID	artificial intelligence or ai or a.i. AND human computer interaction or hci or human-computer interaction AND radiographer or radiologist technologist or practitioner or radiographer	16 results 3 fit the inclusion criteria from the title and abstract
Scopus	user AND interface AND artificial AND intelligence OR ai AND radiograph* OR radiolog*2013–2023	61 results 6 hits found fit the inclusion criteria from the title and abstract
Web of science	TS=(user interface AND radiologist* OR radiographer* AND artificial intelligence OR AI) 2013–2023 Doc type: article Language: English Research Areas: Radiology Nuclear Medicine Medical Imaging	4729 results 120 results fit the inclusion criteria from the title and abstract
Engineering village	user interface AND radiolog* OR radiograph* AND artificial intelligence OR AI (((((artificial intelligence AND radiograph* OR radiologist AND preference) WN KY)) AND (({ja} WN DT) AND ((2023 OR 2022 OR 2021 OR 2020 OR 2019 OR 2018 OR 2017 OR 2016 OR 2015 OR 2014) WN YR))) AND ({all} WN ACT))	1115 total results 35 fit the inclusion criteria from the title and abstract

Table 2
Phrases for Search Strategy.

#	Search Strategy
1	exp artificial intelligence OR ai OR a.i.
2	human computer interaction OR hci OR human-computer interaction
3	radiographer OR radiologist technologist OR practitioner OR radiographer
4	exp user interface
5	1, 2 and 3
6	1, 3 and 4
7	Radiograph*
8	Radiolog*
9	1, 2, 4, 7
10	1, 2, 4, 8
11	2013–2023

Table 3
Inclusion and Exclusion criteria.

Inclusion criteria	Exclusion criteria
Concepts around AI technology in radiology Involvement of radiographers or radiologists or any other healthcare professional that would use AI technology in radiology e.g., Emergency Department clinicians. Evaluation of visual imaging characteristics or user interface of the AI technology Evaluation of the user interface design that should be used.	Focus on opinions and attitudes around AI technology in radiology. Focus on the engineering around AI technology production. No mention of imaging professionals or any other healthcare professional that would use AI technology in radiology clinical practice.

ers during this process were resolved by additional reviewer arbitration.

Some articles from this pool were excluded by both independent reviewers as they predominantly focussed on opinions surrounding AI technology implementation. This process is demonstrated in Fig. 1 with a PRISMA flowchart.

Results

Following author review six papers were acknowledged by consensus to meet the inclusion criteria as demonstrated in Fig. 1. A total of 5921 publications were identified from the 4 databases, though 5889 were removed due to not meeting the inclusion criteria through review of title and abstract and 32 articles were duplicates removed from this stage. 164 articles were screened from their title and abstract and again, 84 of these were excluded as they were missing an element of the inclusion criteria, for example, did not mention AI, though had elements of radiology user interface evaluation. From the remaining 80 papers, and upon further reading the full text, articles did not directly meet the study aims ($n = 74$). The 80 articles were reviewed by reading the full text, with citations also being assessed in detail against the inclusion criteria by two independent reviewers.

The six papers were tabulated to aid the analysis process using demographic headings such as year and location of publications. Headings relating to study methodology such as participant population, sample size, intervention type, outcome measures, mention of auxiliary professionals, standout results and recommendations were also tabulated. Other AI design specific principles such as, type of user interface and perceptions, use of human-centred design principles and use of AI guidelines were noted.

Despite widening the scope of the literature search through inclusion of articles from 2013, there were not any publications relevant to the study aims before 2019. Geographically the spread of the papers was wide, including the Netherlands [31] Australia [24], Canada [22,32]. Argentina [33], and America [34]. These papers had conceptual themes around AI technology in radiology running with avid involvement of end users in the research undertaken or explored. There were elements of evaluation of user interfaces of the AI technology or an evaluation of the designs that should be used, subsequently meet-

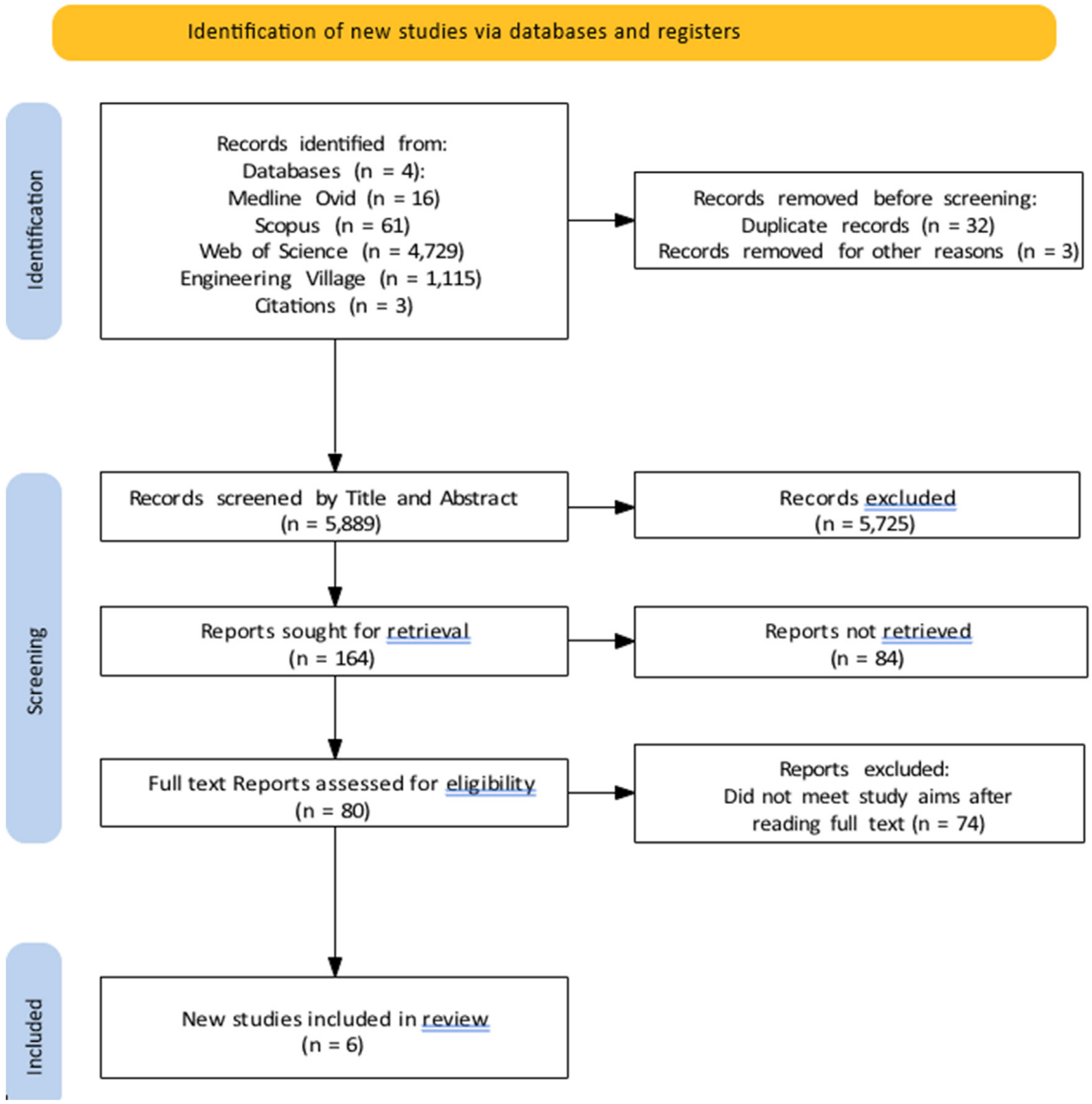

Fig. 1. PRISMA flowchart demonstrating methods.

ing the inclusion criteria. Two of the articles were observational studies [33,34] with the aim of observing radiologists providing radiological reports against a user interface or graphical user interface for educational purposes. Similarly, there were two simulated user testing studies to assess user interfaces for radiologists [22,32]. The diagnostic accuracy study [24] had a similar methodological structure to the simulated user testing studies, though with an integrated 4-week washout period as part of the methodology i.e., a break period from the study. One of the articles was a multiple case study approach of existing AI research to conclude nine roles for radiologists within AI development [31]. Mixed methods were used for four of the papers, with a mix of semi-structured interviews, questionnaires, observational techniques, incorporated into the study design. One study [34] maintained a quantitative focus in their observational study measuring variables such as radiologist image annotation speeds. The participants of all six papers were radiologists, radiology trainees or physicians. Plausibly, all papers were published within the last five years, reflecting the increase in AI technology within radiology. These results can be seen in a table in the Supplementary Material.

The aim of five of the included studies was to review either radiologist/trainee radiologist or ED physician satisfaction [33], usability of an existing user interface for chest x-rays [24,22] or explore the usability of a new graphical user interface for educational [32] or AI application purposes [34]. The multiple case study approach differed from these 5 studies, however still maintained a focus through analysis of machine learning (ML) in medical imaging and the role of radiologist users in AI design [31].

Measuring usability

AI user interfaces are currently a novel area within radiology research, despite the importance user interface design has in AI and allowing use of its capabilities [39]. The Technology Acceptance Model (TAM) was used in one of the studies as a theoretical framework [35], this is a model used commonly within usability studies to test perceived usefulness and ease of use.[48]The System Usability Scale (SUS) was also used as a method in two of the publications used within the review [31,33]. The SUS is considered a quick and standardised questionnaire when testing usability of a product [35]. SUS surveys can also be reduced to scores, with the total score being out of 100. An average score between 80 and 90 is regarded as good/excellent adjective ratings [36].

One of the publications used an adapted SUS, relating to thoughts and attitudes surrounding the chest x-ray user interface, in interview format [22]. Another study [22] used a "Think aloud" method to elicit users' opinions during testing, to ensure their experience was verbalised. They collected detailed data from radiologists. The study [32] exploring MRI graphical user interfaces through a user testing session, also asked participants to complete a SUS survey, to conclude a final average score of 82.5. The study stated this to be comparable to/better than the existing ML UIs found in literature. This was regarded as positive and a measure of high functionality of the UI on MRI images. Another user experience study evaluating a literature AI tool, determined median System Usability scores of 79, 63 and 31 of different software [37] However, comparisons may be difficult due to the technology being for different fields. The study [33] undertaken by 13 professionals (radiologists and ED physicians) also used the SUS scale to evaluate the usability of their chest X-ray AI tool. The results of this indicated that AI was easy to understand with no requirement for special training. However, no scoring system was used in this study, and a few phrases were presented as results, with participants stating their agreement with use of the tool being comfortable and easy to understand. Participants in this study also completed qualitative interviews relating to actual system use, perceived usefulness, ease of use and actual output. These topics are similar to the SUS scale, with the SUS having similar topics relating to efficiency, intuitiveness, ease and satisfaction [36].

Subsequently, results demonstrated that the SUS scale is a quantitative tool that has been used for the usability assessment of AI tools in radiology. However, in two studies in the review, this method was used in conjunction with another qualitative method. An example of this includes interviews, suggesting the SUS measure is not sufficient as a standalone method for the evaluation of user interfaces in radiology. Both quantitative and qualitative methods appear to have a role evaluating ideal user interfaces for AI in radiology.

Ideal output

The ideal chest AI user interface was evaluated in two studies in the form of a simulated workflow or diagnostic accuracy study [22,24].

The study from Canada [22] investigated a regulatory-approved chest radiograph tool, including consideration of the AI user interfaces on the chest radiographs. Though, limited description was provided on the output of this. However, contradictory comments were also made regarding the accuracy of the heatmap [22]. Furthermore, there was confusion around the user interface pertaining to confidence levels from the participants, as they were unsure what the confidence levels related to. There was a suggestion from participants to make the interpretability of this AI user interface feedback clearer. The study from Australia [24] evaluated a text-only user interface for abnormality detection, which had the highest AUC (0.87) within their study, regarding diagnostic accuracy performance. This did not correspond with the participant preferred user interface, where the combined confidence score, text and image overlay/heatmap was the ideal amongst participants. Authors of both studies made suggestions relating to the advantages and preference to the heatmap image overlay interface, due to the information it provided on the location of the abnormality. Despite mixed responses present in both papers, there was a commonality between the two, with some alignment in preference for heatmap image overlays and a suggestion that highly detailed user interfaces within AI are linked to higher preference amongst users.

End users

The value of UI preference of medical imaging AI research ultimately relies on adequate end user evaluation of products and interfaces. One of the studies within the review [24], had 10 radiologist participants (including trainees). Another study [32] had five neuroradiology radiologists including trainees, which related directly to the MRI images they reviewed within the study.

One study [34] also had radiologist participants performing annotation tasks to assess UI components, though similarly to the other study [33], it did not specify the number of total participants in the study. This study [33] also included both radiologists and emergency physicians, as they were regarded as professionals likely to use a chest x-ray AI tool.

Another of the studies [31] interviewed seventeen professionals relating to AI in radiology, including radiologists, managers, and technical professionals, and concluded nine different roles for radiologists within AI sphere. The end users for the majority of the studies included in this review consisted of radiologists. One study [32] measured the time to complete a binary classification task on MRI head images with the radiologist participants against the ML expert as a baseline. One of the studies also [22] noted that the use of heatmaps as a user interface led to an increase in reporting time of 33 % [22]. Another study [34] noted image annotation rates per day and speed per study by radiologists when annotating hip x-rays and CT angiography studies. This study involved the role of radiologists in the image data curation needed for UI and AI development.

This was an interesting measure used in two studies, though there was no positive or negative conclusion relating to this data and instead, may point to radiologist-maintained focus in the research. Despite other professionals using AI tools within radiology and interacting with the user interfaces associated, the

Table 4
Key findings and Recommendations from the scoping review.

Key Findings	Recommendations
Sample sizes no larger than 17 participants	Larger sample sizes are required in the research area
Radiologists were considered the main end users for AI tools in radiology	Inclusion of other healthcare professionals that would regularly use AI in radiology e.g., radiographers
A mix of methodologies for evaluating preferences of AI user interfaces in radiology	Standardisation of outcome measures required, for easier comparisons of tools
System Usability Scales (SUS) are used in evaluating usability of AI tools	Standardise use of SUS with another qualitative method for a complete response relating to preference
Conflicting findings on preferred and most usefully perceived AI UI. Simple designs regarded more highly by participants.	Further research required in the area

literature reflects the importance placed on those involved in the reporting of medical images and does not encompass all potential end-users.

Discussion

Due to the different methodologies between the six studies from five countries, a comparative analysis was unable to be made within this review. Limitations were acknowledged in many of the studies included however, some were ignored. There were insightful recommendations made by all six studies relating to the evaluation of an ideal imaging AI user interface, and the ideal design characteristics as seen in Table 4.

As the area is novel, there is not yet a common methodology noted when reviewing or evaluating ideal imaging AI user interfaces. This could explain the array of methods used within the review. A diagnostic accuracy study [24], simulated workflow observations [22,32–34] and a case study approach [31] were analysed to evaluate the existing research on imaging AI user interfaces. Moreover, there is yet to be a standardised method for assessing usability of AI tools in radiology. Three studies [32,33,36] within this review were noted to use the SUS [32,33], a convenient and simple way to ask questions on perceived usefulness of a tool [36]. However, this was commonly used in combination with a qualitative method such as interviewing. It may be a development of the SUS is needed to gather both quantitative and qualitative data from participants, in the context of AI user interface preference. This could be in the form of open questions to include opinion/preference as part of the usability outcome measures such as the SUS, that was used in three out of six papers. Two studies in the review did not mention the sample size within their methods [32,33], subsequently meaning the repeatability and generalisability of the results is reduced. The remaining four studies had relatively small sample sizes, no larger than seventeen, with 10 radiologists being the dedicated sample size amongst two studies [22,24,31,32].

Further to this, none of the studies referred to radiographers as end users, or healthcare professionals that would commonly interact with AI user interfaces. This could point to an outdated or exclusive culture when considering research in the radiology technology integration field and the inclusion of radiographers. Radiographer research has suggested the existence of tribalism and differences between interprofessional cultures within clinical environments [42]. Additionally, considering the geographical spread of the six studies, there are expected cultural and sub-cultural differences relating to professional roles and autonomy, such as radiographers. Research has identified the impact of socio-economic and cultural environments on radiographers, especially relating to role advancement across different countries [43]. This is interesting as in the exploration of radiologist and radiographer perceptions surrounding AI integration, opinions are harmonious between the professional groups [44], indicating similarities. The exclusion of allied healthcare professionals such as radiographers from radiology AI UI design research is unfavourable due to the implications this has again on the generalisability of the results of the research in the review. This is with a smaller and exclusive sample not having representation of the wider imaging professional population [38]. From the articles within this review, there is a lack of inclusion of radiographer and other auxiliary professionals within medical imaging, in the exploration of user preference of AI UI.

Overall, the findings from the review indicated that heat map image overlays were suggested as an advantageous user interface to understand the location of the abnormality by participants in one of the studies [22]. This is supported by research as heat map image overlays have been suggested as a way to increase transparency or interpretability of AI. This is through the display of more information on the AI model's decision making process [45,46]. However, contradictory comments were made on the accuracy of the heatmap UI identifying pathology. Similarly, confidence levels were preferred in combination with heat map UI and textual UI, from participants in one of the studies [24], though participants from another study [22] suggested they could be confusing and needed more detail when provided as the user interface. The studies evaluating AI UIs had clear recommendations, suggesting simple non-intrusive designs that capture user attention would be received more favourably by radiologist users [22,24]. However, there was a suggested fine line between capturing user attention and interfering with workflow, and this was suggested to be considered in the design of imaging AI UIs [33]. It could be suggested that further research in this area to evaluate these UIs over a longer period, to evaluate preference in more detail.

Furthermore, the results from one study [24]. indicated radiologist user preference as a combination of combined text, AI confidence score and heat map image overlays. This was interesting due to a discrepancy between user preferences and performance, with radiologists reporting more accurately when using a text only user interface. Finally, there is an identifiable gap in robust research on preference for imaging AI UI. There is an indication that more research is required on the subject area with larger sample sizes to increase the validity of the results.

Limitations

Due to the range of reporting methodologies in the field, it was not possible to complete a systematic review. Additionally, because of the aims of the scoping review, the inclusion criteria were strictly defined, reducing the number of studies included. This in turn, may have affected the overall findings of the review. Only four databases were used for searches, with three healthcare focussed and one computing and engineering focussed. It may be suggested that a wider search may have resulted in more articles for review, however these databases were carefully selected based on their wide scope and following discussion with a subject specialist librarian. Despite these limitations, the study has identified a requirement for further research on the topic of medical imaging AI UIs with an inclusion of radiographers as end users.

The six studies used in the scoping review also had limitations within themselves relating to methodology. All six studies had small sample sizes no larger than 17 participants amongst all studies [22,24,31–34]. One of the studies was also funded by an AI vendor [24]. Additionally, one study [22] used the "Think-Aloud" method which may have limitations as not every cognitive process can be verbalised [40].

Conclusion

Medical imaging AI UI research is essential for the acceptability of AI technology into radiology departments. Within this review, studies were extremely varied in nature, relative to their aims, methodologies and ultimately findings. Due to the research topic, it was difficult to find methodologically similar studies, and therefore the review included studies evaluating UIs used for the formation of imaging AI and studies evaluating AI UIs themselves. It is evident that there are design characteristics favoured by users such as heatmap image overlays and confidence levels with more detail. Interestingly, research has also suggested that there is a discrepancy between user performance and user preference, and more research is needed to investigate this relationship. Due to the limitations of the research used there is a need for further research on the topic to consolidate user preference for imaging AI UI.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmir.2025.101866.

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