Radiography 30 (2024) 474–482

Contents lists available at ScienceDirect

Radiography

journal homepage: www.elsevier.com/locate/radi

Systematic Review

A scoping review of educational programmes on artificial intelligence (AI) available to medical imaging staff

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ARTICLE INFO

Article history:
Received 26 October 2023
Received in revised form
29 December 2023
Accepted 30 December 2023

Keywords:
Artificial intelligence
Education
Medical imaging
Radiology
Radiography

ABSTRACT

Introduction: Medical imaging is arguably the most technologically advanced field in healthcare, encompassing a range of technologies which continually evolve as computing power and human knowledge expand. Artificial Intelligence (AI) is the next frontier which medical imaging is pioneering. The rapid development and implementation of AI has the potential to revolutionise healthcare, however, to do so, staff must be competent and confident in its application, hence AI readiness is an important precursor to AI adoption. Research to ascertain the best way to deliver this AI-enabled healthcare training is in its infancy. The aim of this scoping review is to compare existing studies which investigate and evaluate the efficacy of AI educational interventions for medical imaging staff.
Methods: Following the creation of a search strategy and keyword searches, screening was conducted to determine study eligibility. This consisted of a title and abstract scan, then subsequently a full-text review. Articles were included if they were empirical studies wherein an educational intervention on AI for medical imaging staff was created, delivered, and evaluated.
Results: Of the initial 1309 records returned, n = 5 (~0.4 %) of studies met the eligibility criteria of the review. The curricula and delivery in each of the five studies shared similar aims and a 'flipped classroom' delivery was the most utilised method. However, the depth of content covered in the curricula of each varied and measured outcomes differed greatly.
Conclusion: The findings of this review will provide insights into the evaluation of existing AI educational interventions, which will be valuable when planning AI education for healthcare staff.
Implications for practice: This review highlights the need for standardised and comprehensive AI training programs for imaging staff.

Introduction

The Information Age[1] has been a driving force for healthcare innovation for around 40 years, with access to vast amounts of data and technology which has equipped the workforce with the tools and power to transform healthcare. The advent of artificial intelligence (AI) has been one of the most revolutionary aspects of this age. The ubiquity of AI has led to government, professional body, and regulatory body action to address the necessity for integration and regulation of AI, in the form of guidelines published.[2–5] As interest in and use of AI has grown, some authors have claimed that AI could render radiology as a specialism obsolete or automate many roles within medical imaging, ultimately leading to job losses.[6–8] These claims have thus far proven to be redundant, but a legacy of trepidation towards AI remains for some.[7–10].

Numerous studies positing the capabilities of AI have been published, with many claiming algorithms can be as competent as their human counterparts.[11–17] However, many sceptics and proponents alike have raised a concern over the claims that have been made in such studies, citing limitations which could affect the validity, generalisation, and reproducibility of results.[18–20] The aforementioned research aiming to verify the capabilities of AI has led to an increase in qualitative research seeking to ascertain the opinions of various facets of the healthcare workforce in relation to

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https://doi.org/10.1016/j.radi.2023.12.019

AI[77]. [10,21–23] These studies add value to the discussion and implementation of AI. Themes recurring in much of the recently published literature indicate that whilst the earlier claims of a bleak future in medical imaging have not had a detrimental effect on staff outlook on their careers,[7,23,24] there is still a perceived reluctance to utilise it clinically.[21,24–26]

Common findings in these studies indicate that staff feel that they do not know enough about AI to confidently implement it safely and effectively in practice. Despite the use of AI tools currently increasing in clinical practice, there is a self-reported lack of ability to understand, critically appraise and ethically apply these tools in routine clinical practice.[9,21,23] AI guidance[2–5] state that education on AI is essential for its successful implementation. Despite this guidance, there is a paucity of research to investigate the current landscape of education on AI for healthcare staff.

AI education has also been recommended as part of The Topol Review[27] in the UK – both as part of pre-reg healthcare programmes, and as a continued development of the skillset of the current workforce. From September 2023, the updated Health and Care Professions council (HCPC) Standards of Proficiency for radiographers[28] state that clinicians must be able to demonstrate awareness of the principles of AI and its application to practice, yet there has been no investigation into the current status of educational provision. To mark the 75th anniversary of the founding of the National Health Service (NHS), it was recently announced that a £21 million AI Diagnostic Fund is to be made available to Trusts allowing them to accelerate the deployment of promising AI tools to help patients receive treatment more quickly.[29] Citing that the NHS spends £10 billion annually on medical technology and that the global market is forecast to reach £150 billion in the next year, this investment will be of enormous benefit to patients. In this announcement, no indication is given of how the NHS plan to prepare staff to understand and effectively use AI. Whilst claims that future graduates will have AI education embedded in their undergraduate training, specific details of how this will be undertaken are lacking. In a survey of UK higher education institutes (HEIs), preliminary findings show that 70 % *($n = 14$)* claim to have already introduced AI to the curriculum, however when asked to indicate how it has been introduced, details given were vague, including “a lecture to 2 nd year”, “a lecture to L6”, and “L4-6 physics modules”.[30] Further to this, medical imaging lecturers and practice educators were surveyed about their thoughts on and preparedness for delivering AI education. 52 % *($n = 17$)* said that their institution has introduced AI education, but when asked to provide details answers were vague, with examples such as “increasing number of students including AI in dissertations” and “virtual reality assessments in labs”. Only 14 % ($n = 4$) of lecturers and practice educators indicated they have completed some formal training on AI – examples given ranged from modules as part of a MSc in biomedical engineering to free online coding skills. 33 % ($n = 11$) indicated they are using AI in their role but only half of those say they received training on how to operate the AI technologies. That only 14 % ($n = 4$) of respondents claim to have received any formal AI training indicates that there is a serious lack of education on AI available to clinical imaging staff. Alongside the updated HCPC standards of proficiency which now state that registrants must demonstrate an awareness of AI and new technologies, these figures show there is a demonstratable necessity for AI education for the medical imaging workforce. Whilst some endeavours to undertake the process have commenced, these have been described as piecemeal and unregulated, inaccessible, conversely too low-level, and too complex, and lacking in hand's-on practice.[9,25,26,31–33]

Clinical staff must exercise caution and ensure that AI does not encroach into clinical practice unchecked. Some studies have found there could be a tendency for over-reliance and trust in AI to perform tasks usually requiring human input.[34] This could be due to lack of confidence in ones' own skill,[24] time constraints or other work pressures.[35] It would be reckless to place faith in technologies which, although purported to perform accurately, faster and without fatigue, are still fallible. As with all new ways of working, there must be a time of learning and adjustment. However, it could be considered that an issue with the rapid deployment of AI solutions is that there has been no time to learn or adjust. These technologies are already here and in clinical use. Manufacturers and vendors offer assurances that they can perform to tested, specified levels.[13,15] However, as clinicians guided by professional codes of conduct and ethics, users must practice with the best interest of patients at the core of their work.[28]

A Canadian scoping review[36] attempted to examine and summarise the range of AI educational offerings for healthcare professionals at the time. This review appeared comprehensive, reporting on a total of 41 programmes mainly from the United States but with one each in Canada, Mexico, and France. However, the criteria used to screen the published literature was broad and the data analysed was composed of a mixture of empirical studies, narrative articles, opinion pieces, and conference abstracts. Further to this, the focus of some of the included data does not pertain specifically to AI, with topics such as medical bioinformatics and Bayesian Networks encompassed. These are considered higher level concepts, beyond the realm of basic AI knowledge that would be applicable for novices to the topic of AI.[37] Moreover, recognising the limitations of a previous attempt to review the literature – where flaws in data collection and analytic methods were evident – it becomes clear that results identifying heterogenous metrics used to evaluate courses are significant, and meaningful comparison of the data was not achievable. Considering these challenges and to address the subsequent limitations, this scoping review is designed to provide valuable insight into the landscape of research on AI educational interventions for medical imaging staff globally. By doing so, it aims to contribute substantively to the ongoing conversation about the future of medical imaging education internationally.

Methods

A methodological framework proposed by Arksey & O'Malley[38] was followed to conduct the review. This involved five stages: (1) identifying the research question; (2) identifying relevant studies; (3) selecting studies; (4) charting the data; and (5) collating, summarising, and reporting the results.

Relevant keywords related to AI and medical imaging education were identified (see Table 1) and used to search the databases Medline and the Cumulative Index to Nursing and Allied Health Literature (CINAHL) in July 2023. The initial searches yielded 1446 results (see Fig. 1). A total of 110 duplicate records were removed at this stage. The remaining records underwent a screening process, starting with title screening and followed by abstract screening. A total of 1266 records were excluded during this process. The primary reason for exclusion was that the papers did not align with the focus of AI education. While the terms ‘AI’ and ‘education,’ or their synonyms, appeared somewhere in the text of these papers, they did not pertain to education on AI in the context of medical imaging. Many excluded papers were studies evaluating various AI technologies and algorithms in clinical settings, for example investigating the sensitivity and specificity of an AI tool to detect a pathology. Other excluded records included conference abstracts and editorials, which did not meet the inclusion criteria for empirical studies. After the screening process, 70 full-text articles were assessed for eligibility. Our inclusion criteria (see Table 2)

Table 1
Search strategy.

#	Search term
1	exp Artificial Intelligence/
2	((“artificial intelligence” or ai) not “machine learning” not ml not “deep learning” not dl)
3	#1 or #2
4	exp Radiography/
5	((radiograph* or “radiograph* technologist*” or “radiograph* technician” or “diagnostic imag*” or “medical imag*”) not diagnosis not treatment not disease).tw.
6	Radiotherapy/
7	((“radiation therap*” or radiotherapy or radiother* or “radiation oncolog* or radiotherapy technician” or “radiation technologist”) not diagnosis not treatment not disease).tw.
8	exp Radiology/
9	((radiology or radiologist or radiolog*) not diagnosis not treatment not disease).tw.
10	#4 or #5 or #6 or #7 or #8 or #9
11	exp Education, Professional/
12	exp Teaching/
13	exp Curriculum/
14	(teaching or curricul* or education* or student* or module* or “professional develop*” or CPD or CME or certific*).tw
15	#11 or #12 or #13 or #14
16	#3 and #10 and #15
17	limit 16 to english language
18	17 and “Journal Article”.sa_pubt
19	limit 18 to (journal article and “humans only (removes records about animals)”)

encompassed specific keywords related to AI and medical imaging education. We focused on studies that met these criteria to ensure alignment with the scope of our review.

Results

Ultimately, only 5 papers met the inclusion/exclusion criteria of novel educational interventions for medical imaging staff that have been designed, delivered, and evaluated. However, works of relevance to the topic have been cited throughout this paper. Of the five studies included in this review, two were delivered in the USA,[39,40] two in Germany[41,42] and one was delivered in the United Kingdom.[43] All five studies were educational interventions; four were targeted to medical students, radiology residents and adjacent professions such as attending physicians, medical doctor (MD) PhD researchers, non-medical PhD researchers and MDs. Only one was for radiographers.[43] No other categories of medical imaging staff were eligible for the other four studies included in this review as the programs were designed and delivered as initiatives specifically for doctors. A finding of note from Schuur et al. in their 2021 systematic review[25] was that only 7 % ($n = 7$) of the one hundred training initiatives they reviewed explicitly included radiographers as part of the target audience. For the full population breakdown for each study see Table 3. Population size per study ranged from $n = 5$ to $n = 120$ per lecture/session/day.

Findings

Both studies conducted in the United States[39,40] and one German study[41] explicitly stated that their research aimed to address an identified gap in AI training for medical and radiology students. In contrast, the remaining two studies did not explicitly indicate in their study aims that they sought to fill a recognised need for AI training among medical imaging staff.

Despite their limited number, these studies were conducted within a three-year timeframe and offer insights into current trends within the medical imaging community. The increasing emphasis on AI usage in medical imaging practice reinforces the need for further research in this area. As mentioned earlier, consensus in AI opinion research highlights one of the major challenges in AI adoption—i.e., the lack of knowledge among clinicians. The main study characteristics have been summarised (see Table 3) for clarity and ease of reference.

Mode of delivery

Four of the studies included in this review employed a combination of online and in-person didactic elements, along with synchronous and asynchronous content delivery methods. The necessity to adopt this approach was influenced mainly by restrictions imposed during the worldwide lockdown and social distancing protocols, as dictated by the World Health Organisation and local government guidance during the Covid-19 pandemic.[44] In the Perchik study[40] it was noted that whilst originally in-person lectures and technical demonstrations were planned, the switch to online lessons was well received by participants and was so successful that it allowed the programme to encompass 9 radiology residency programmes across the USA, enabling the provision of the intervention to a greater range of participants. Lindqwister et al.[39] do not offer any specifics as to the mode of delivery. It can, however, be assumed that the intervention was delivered entirely in person as when discussing the limitations of their study, it is mentioned that a transition to online learning might have resolved the issue with high attrition in later sessions.

A ‘flipped classroom’ approach was utilised in three studies.[41–43] This teaching approach, wherein the traditional lecture and homework elements of a course are reversed, explain a bit more has been reported to allow for more active and collaborative learning during class time.[45,46] Another benefit typically accredited to the system is that there can be provision for more individualised support for students who may need additional help with the material. In a flipped classroom, students are introduced to new material outside of class, typically through asynchronous methods like videos or readings.[45,47] Synchronous class time can then be used for activities that allow students to apply and deepen their understanding of the material.[47,48]

It appears that the flipped classroom approach was favoured by participants in the Hedderich et al. study,[41] as post-course feedback was said to be positive. Participants in the van de Venter et al. study[43] described sometimes contradictory opinions in response to the mode of delivery. The authors identified four themes in their analysis of this: 1. Participants' professional and educational background influenced their experience 2. A meaningful learning

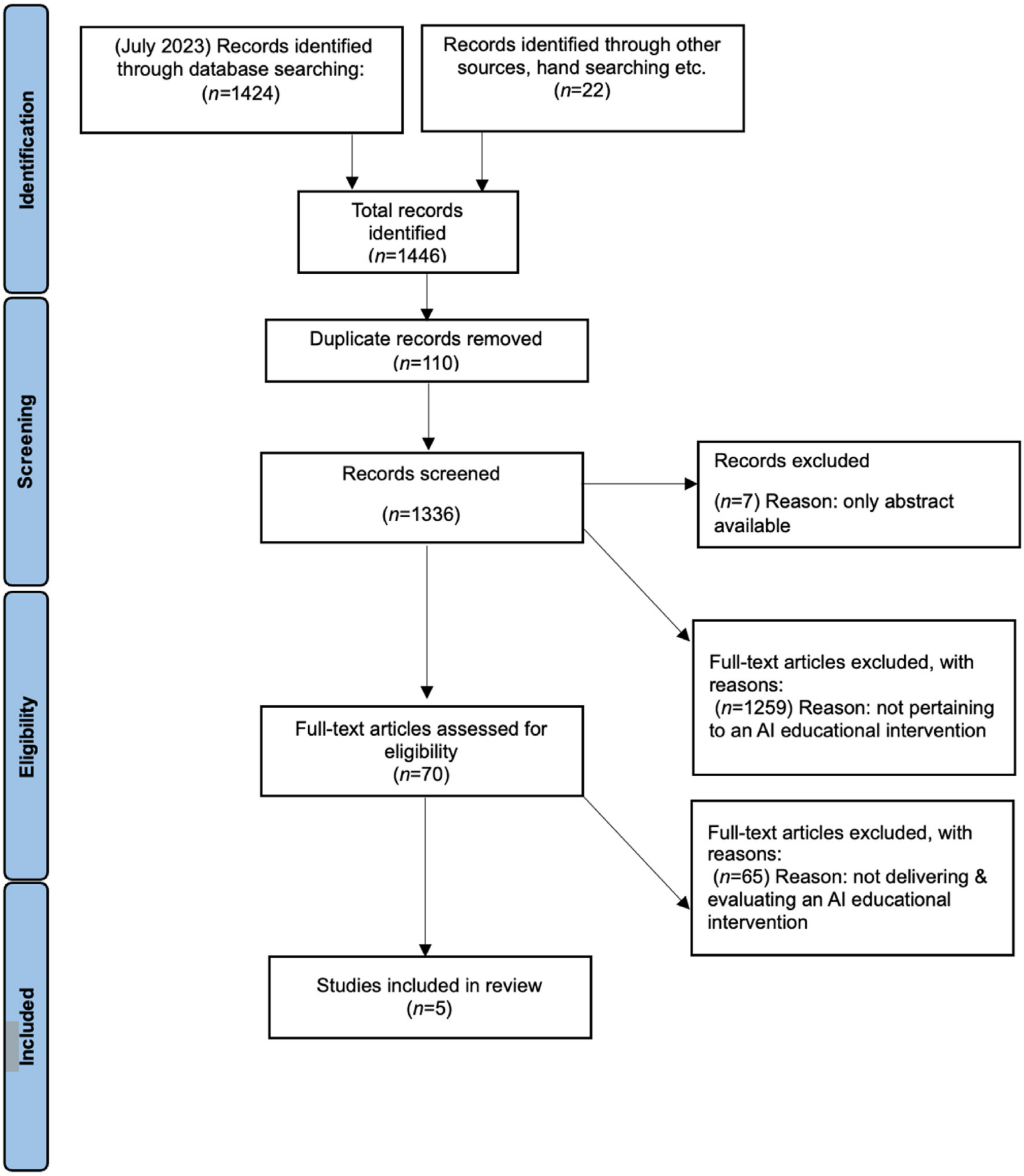

Figure 1. PRISMA flow diagram.

Table 2
Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
Main subject AI education or curriculum	Tangential to AI education e.g., informatics, programming, algorithm testing
Within medical imaging domain i.e., for radiographers, radiotherapists, radiologists	Outside of medical imaging domain
Focus on level of knowledge, aptitude, or ability to use AI	Focus on attitudes, perception, or opinions on AI
Delivers and evaluates an educational intervention about AI	Uses AI to teach or evaluate an educational intervention

experience 3. Barriers to learning and threats to module status and 4. The ideal introductory AI module. Within these themes, the flipped classroom and online delivery was both praised and problematised by participants. The cost-effectiveness and flexibility of the approach were highlighted as beneficial, but also as a barrier to learning and development owing to isolation from peers. Lindqwister et al.,[39] Perchik et al.[40] and Laupichler et al.[42] do not note any specifics or feedback on their participants' preferred mode of delivery. These studies do, however, mention high attrition rates in later sessions and low response rates to post-evaluation feedback, with Lindqwister hypothesising that the poor attendance towards the end could indicate a preference for online learning.

Table 3
Summary of study characteristics.

Author(s)	Lindqwister et al.	Hedderich et al.	Perchik et al.	Lauplicher et al.	van de Venter et al.
Year	2020	2021	2022	2022	2023
Country	USA	Germany	USA	Germany	UK
Aim	To address the unmet need for resources to gain a basic understanding of AI via "formal integration into residency training"	To address to the problem of "educational offerings tailored to the need of medical professionals are scarce" … yet "successful adoption of AI … requires them to understand the underlying principles and techniques"	"To address the need for practical and accessible AI education in Radiology"	"To design and evaluate a novel AI-course for medical students"	To evaluate and discuss a postgraduate module on AI for radiographers
Population	Radiology residents at Dartmouth College	Doctors, medical students, PhD and non-medical researchers at Technical University of Munich School of Medicine	Radiology residents, medical students & attending physicians across 9 radiology residency programmes in the South-East & Mid-Atlantic US	Medical students in semester 3 or higher at Bonn Medical School	Students who had enrolled and completed the module
Sample size *(n)*	$n = 5–12$ (per lecture)	$n =$ *50-120* (per day)	$n =$ *50-120* (per day)	$n = 24$	*(no total provided in the text for number of participants in the module but 7 completed the qualitative study)*
Method	*AI-RADS* course	*AI for Doctors: Medical Imaging* course	*AI Literacy Course*	*KI-LAURA* course	*An Introduction to AI for Radiographers* course
Developed by	Medical student fellow in radiology	Medical and non-medical imaging researchers/lecturers	Panel of 3 attending radiologists & 1 lead radiology resident each with 4–10 years' experience in AI research & education	Radiology, ophthalmology & neuroradiology experts	City, University of London
Intervention type	One monthly didactic session; One monthly journal club with self-study guide and academic paper	Flipped classroom delivery; online asynchronous learning materials & synchronous lectures	Online synchronous didactic lectures; 'Hands-on' session	Flipped classroom delivery; online asynchronous learning materials, synchronous lectures & tutored exercises	Flipped classroom delivery; online synchronous tutorials/ discussion & asynchronous peer support forum
Duration	7 months	12 weeks	One week	One semester	12 weeks

This preference has been noted in numerous studies post-pandemic,[49,50] with reasons cited including the flexibility it offers and reduced travel time allowing for better study/life balance. Conversely, some studies have also reported some negative opinions regarding online learning,[51,52] with participants citing isolation, distraction and poor focus when engaging with remote learning.

The curriculum offered in the five studies (see Table 4) ranged from basic AI terminology[40,41,43] to coding lessons[40,41] and background and applications of high-level concepts such as naïve Bayes and K-Nearest Neighbour.[42] All five studies also state they provided instruction on clinical applications of AI, with only Perchik et al.[40] detailing the specific medical imaging domains included. Van de Venter et al.[43] specified their lessons comprised tuition on clinical applications of AI in both projectional and cross-sectional imaging, in a range of modalities. No study mentions any content regarding image acquisition. Perchik et al.[40] and Laupichler et al.[42] both indicate participants had hands-on practice, with the former given time to practice interpreting a set of diagnostic images without AI assistance, then comparing their interpretation to AI to assess how human interpretation differs from AI. Participants in the Perchik et al. study[40] gained experience of lesion segmentation, interpreting images flagged by AI for follow-up and working with AI generated reports. The Lindqwister et al. study[39] related each of the algorithms covered to an application in clinical radiology, whilst Hedderich et al.[41] delivered special focus sessions highlighting particularly interesting fields of AI in medical imaging and how they translate to clinical practice. No specific information was given on how clinical applications were covered in the van de Venter et al. study,[43] but participant feedback states that an introductory module "should have more examples of clinical applications". Interestingly, none of the studies specified provision of any material pertaining to AI applications in musculoskeletal imaging.

Outcomes to assess effectiveness

Four studies used self-reported means of assessment to evaluate the impact of their intervention, ranging from ability to describe topics, understanding of concepts and applications, confidence in reading literature pertaining to AI in medical applications and comparative self-assessment of knowledge (CSA). As noted in Table 5, all the studies reported success, participant satisfaction and positive feedback. Lindqwister et al.[39] demonstrates increased participant confidence in reading AI in radiology journal articles week-on-week, although this was not statistically significant. There was, however, significantly enhanced confidence in participants' ability to describe concepts that were mapped to the learning outcomes of the course (*$p < 0.04$*), which the authors describe as 'content mastery'. Hedderich et al.[41] used Likert-scale ratings for participants to rate their self-perceived skill on measures including their ability to understand Python code, concepts in linear algebra, creating code for statistical analysis, and applying an algorithm in a

Table 4
Course content.

Author(s) Course	Learning Outcomes	Curriculum
Lindqwister et al., 2020 AI-RADS	Describe foundational algorithms … their intellectual underpinning … applications to practical radiography. Proficiently reading journal articles on AI in radiology. Identify potential weaknesses in AI design, database features & performance reports. Identify areas where AI techniques can be used to address problems. Describe different ways information can be abstractly represented and exploited. Demonstrate a fluency in common “buzzwords” in artificial intelligence.	Probability: Naïve Bayes. Pixel Math: K-nearest neighbour. Dimensionality: K-means. Ensembles: Random Forest. Vector Manipulation: The Perceptron. Gradients: Support vector machines. Complexity: Neural networks.
Hedderich et al., 2021	None specified.	Introduction to machine learning: Historical context, systematic considerations, and basics of linear algebra. Introduction to artificial neural networks: what can AI learn? Basics of linear algebra. Applying AI to imaging: special considerations for medical imaging. Advanced learning methods with artificial neural networks: unsupervised learning. Generative adversarial networks and medical image formats. Critical appraisal of AI studies in radiology: reporting metrics and paper analysis Structured reporting in radiology. Explainable AI in medical imaging. Computational pathology. AI in dermatology. AI in neuroscience: Ethical, legal, and societal aspects. Ethics in AI.
Perchik et al., 2022	Core concepts (evaluations mapped to these): Training/testing/validation data. AI/ML/neural network hierarchy. Ethics of AI. Algorithm bias. Upstream AI. Overfitting. Black box.	Introduction to terms and methods. AI in neuro radiology. AI in breast imaging. Economics and ethics. AI in abdominal imaging. Thoracic medicolegal issues with AI discrepancies. Algorithm bias. Working on AI project. Integration of AI and future in radiology.
Lauplicher et al., 2022	None specified.	AI Fundamentals: Explains key AI terms, including Machine Learning and Deep Learning Imaging Techniques: Covers various imaging methods and addresses quality assurance and diagnostic challenges. AI in Radiology: Explores AI applications in radiological practice, current research, and its impact on human radiologists. Hands-On Learning: Provides practical exercises with a DICOM viewer and AI in radiology. Ophthalmology Imaging: Focuses on imaging techniques in ophthalmology and diagnosing common eye diseases. AI in Ophthalmology: Examines AI's role in ophthalmological diagnosis, its pros and cons, and ethical considerations. Python AI Basics: Introduces AI algorithms in Python with an eye-related example and compares them with participants' abilities. Neuroradiology Modalities: Explores common imaging modalities in neuroradiology and typical findings. AI in Neuroradiology Programs: Discusses AI's use in commercial neuroradiology software and evaluates its benefits. Practical Group Exercises: Engages participants in hands-on AI activities in neuroradiology. Final Assignment Prep: Provides guidance on the course's final assignment, including content and resources, and outlines the course evaluation process. Final Assignment: Requires participants to create an informative interview video on unexplored AI topics from the course.

(continued on next page)

Table 4 (*continued*)

Author(s) Course	Learning Outcomes	Curriculum
van de Venter et al., 2023	None specified.	Clinical applications of AI in projectional and cross-sectional imaging, reporting, ultrasound, mammography, and interventional radiology. Basic computer science fundamentals underpinning algorithms and associated workshop for hands on work. Impact of AI on workflow in medical imaging. Ethical considerations associated with AI. Patient and healthcare acceptability of AI. Industry-led workshops to introduce state of the art AI applications and foster networking.

Table 5
Measures and outcomes.

Author(s)	Reported outcome measures	Key findings
Lindqwister et al., 2020	Pre- & post- didactic session questionnaire on self-reported Likert scale measuring perceived understanding of concepts, with questions mapped to learning objectives. Post-journal club questionnaire on self-reported Likert scale measuring self-reported confidence to understand academic papers relating to topic.	Statistically significant increase in mean AI knowledge ($p = 0.042$) *by Wilcoxin Sign-rank test.*
Hedderich et al., 2021	Pre- and post-course questionnaires measuring opinions of AI on Likert scale. Self-perceived AI-related skills. General course evaluation.	Attitudes were “very optimistic” before and after. Deeper knowledge reduced optimism with respect to perceivable patient benefits ($p = 0.020$). Self-assessed skill increased significantly post-course. Feedback on course content was positive.
Perchik et al., 2022	Pre- and post- course survey measuring self-reported familiarity with AI. Graded pre- and post- course evaluation test 15 questions.	Low-level of exposure to AI and relevant training. Statistically significant increase in objective understanding of AI. Increased subjective understanding of AI terms & applications.
Lauplicher et al., 2022	‘Then’ and ‘Now’ self-reported questionnaires using adapted version of medical AI readiness scale for medical students (MAIRS-MS). Comparative self-assessment (CSA) gain. General course evaluation.	Statistically significant increase in perceived AI readiness. Increased CSA gain on AI readiness.
van de Venter et al., 2023	Thematic analysis of focus group discussions and semi-structured, individual interviews.	Four themes describing the participants' experience of the module were identified: 1. Participants' professional and educational background influenced their experience. 2. A meaningful learning experience. 3. Barriers to learning and threats to module status. 4. The ideal introductory AI module.

clinical setting. All self-perceived skills were noted to have improved with p-values for each ranging from 0.001 to 0.042, indicating varying levels of statistical significance. Participants in the Perchik et al. study[40] showed a significant ($p = 0.042$) increase in post-course evaluation scores and modest but statistically significant ($p = <0.01$) increase in comfort with fundamental AI terminology and methods. Laupicher et al.[42] assessed the success of their course using an adapted version of the Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS), which maps AI readiness to four factors: cognition, ability, vision and ethics. The main change was to allow for the instrument to be administered retrospectively, with participants instructed to complete a post-course version and a “then” version referring to their self-assessment of before the course. This will provide a measure of change in AI readiness. The original MAIRS-MS was psychometrically assessed and had acceptable internal consistency (Cronbach's alpha coefficient = 0.88). The adapted versions' Cronbach's alpha was reported as 0.93 (“then”) and 0.88 (“post”). The authors also calculated a measure of comparative self-assessment (CSA) gain to account for the individual readiness of participants, as well as the nature of reporting t-tests (i.e., some changes will likely occur following participation in an intervention). The study reported an overall significant trend ($p<0.001$) in MAIRS-MS scores from “then” to “post” course. CSA gain averaged across all items was reported only to be acceptable (55.6 %) and scores across individual items ranged from 28.3 % to 73.5 %. Participants indicated satisfaction with the overall course and rated the self-study elements and classroom sessions over the final assessment. The van de Venter et al. study[43] chose to employ a qualitative thematic analysis, rather than a quantitative evaluation of participants' ability, knowledge, or awareness of AI pre- and post-intervention. This study evaluation also differed in that it sought feedback from its faculty as well as students, and utilised semi-structured interviews as the data collection method. This holistic approach was used as it allowed for gathering in-depth information and an overview of both student and faculty experiences of the module. Whilst this allowed for a reflective and interpretative account of individual's own impressions of the content and delivery, it does not provide data that can be used to compare the impact of the module with the others included in this review.

Discussion

All included studies acknowledged some limitations and recommended ways in which consequent studies could be improved, as well as offering insight into the positive aspects of their interventions. The populations and participants in the included studies did not vary greatly, with most being medical students or radiology residents (see Table 2). The metrics used, and outcomes measured also display some homogeneity (see Table 5); for example, the use of pre- and post-intervention surveys was implemented in all but one study, which instead conducted a qualitative analysis of their intervention.[43] Likert scales were implemented in the four studies which employed quantitative analysis,[39–42] but there was no consistency between these studies in terms of what they measured, ranging from self-perceived ratings for skill,[41] learner confidence and comfort in reading AI literature,[39] satisfaction with different delivery methods[42] and interest in and exposure to AI.[40] Due to the disparity between measured outcomes, it is not possible to accurately compare these studies. However, the consensus indicates that AI education has been demonstrated to yield positive results across the studied populations. A greater level of standardisation in the reporting of the studies would be required to allow the positive and negative points in each to be objectively measured against the rest, or for their success to be weighed against other. The use of validated instruments would be of benefit to allow for adequate comparisons and conclusions to be drawn. The adapted MAIRS-MS, utilised by Laupichler et al.[42] appears to be the most robust tool of the studies included herein, however the authors highlighted that discrepancies between the content of their KI-LAURA course and some of the individual items in MAIRS-MS could explain the large variance in CSA gain within their study. Whilst the KI-LAURA course was tailored to basic understanding of AI terminology and its importance and relevance to the future of medical imaging, the MAIRS-MS contains items pertaining to statistics which are not considered to be central to basic AI literacy.[37] Furthermore, the instrument is designed to measure AI-readiness as a status quo and despite being adapted by the authors to attempt to address the need to measure a change in AI readiness, no confirmatory factor analysis could be completed due to the small sample size of the study. Finally, the instrument is designed to gauge AI readiness, a concept that reflects participants' self-reported preparedness to use AI in their place of work. The point of the educational interventions described herein is not to measure changes in readiness, but rather to assess the impact of said intervention on skills, knowledge, and ability. It would be more pertinent if an instrument was developed to measure those attributes, which could also be called ‘AI literacy’.

Whilst each of the studies in this review has reported positive findings and degrees of success in achieving their individual aims, the results are not generalisable due to a range of factors and limitations. This includes incongruous reporting between all studies, small sample sizes, differing objectives and unvalidated measures, varying level of curricular intensity, range of topics covered, differing participant backgrounds. This, coupled with the fact only a meagre number of published studies were available for inclusion in this review indicate that there is an abundant need for more research into this area. Further research is warranted in that a level of parity must be sought in what is offered on any curriculum for AI education in medical imaging, and how the corresponding impact is measured must also be investigated. With the changes to the HCPC Standards of Proficiency[28] and the imminent arrival of AI technologies in hospitals across the UK,[29] it is essential that staff and students receive sufficient educational interventions to ensure they are prepared for working alongside these technologies. Failure to deliver this will result in disparity and inequity in learning opportunities which could ultimately cascade to poor outcomes for patients and detriment to the reputation of the professions concerned.

Limitations

Due to the nature of a scoping review, quality of the included studies was not assessed. The lack of suitable studies for inclusion is also a limiting factor, however given the nature of the topic and the abundance of quasi-related literature, it was necessary that the remit for inclusion be strict. Despite these limitations, the review has highlighted a gap in the literature for design and delivery of quality educational interventions, and the subsequent evaluation of such.

Conclusions

AI education for medical imaging staff and students should be a top priority for Health Trusts and universities. It is essential for the development of professional roles and the future of medical imaging professions. Appropriate education is crucial for addressing ethical concerns and tackling reluctance to pursue medical imaging as a career. Also, the potential consequences of failing to ensure AI education maintains pace with technological advances are significant. Therefore, it is imperative that AI education is prioritised for imaging staff to ensure the workforce are adequately prepared for the future of medical imaging. The importance of clear and succinct educational interventions for medical imaging staff is evident in the literature. The numerous articles in circulation emphasise the importance of informing the workforce and its key role in resilience and patient care. Furthermore, the review of the literature suggests that there is a clear need for more empirical research focused on the design, content and validation of educational interventions or curriculum additions. Little work has been done in this area to date and future research should take these factors into account to inform evidence-based approaches to AI education.

Conflict of interest statement

None.

Acknowledgements

This work was supported by a College of Radiographers Industry Partnerships Scheme [grant number 229 (AI)].

References

1. Drucker P. *Age of Discontinuity: guidelines to our changing society*. 2nd ed. New York: Routledge; 2017.
2. Tang A, Tam R, Cadrin-Chênevert A, Guest W, Chong J, Barfett J, et al. Canadian association of radiologists white paper on artificial intelligence in radiology. *Can Assoc Radiol J* 2018;**69**(2):120–35. https://doi.org/10.1016/j.carj.2018.02.002.
3. Joshi I, Morely J, editors. *Artificial Intelligence: how to get it righ. Putting policy into practice for safe data-driven innovation in health and care*. London, UK: NHSX; 2019.
4. Malamateniou C, McFadden S, McQuinlan Y, England A, Woznitza N, Goldsworthy S, et al. Artificial Intelligence: guidance for clinical imaging and therapeutic radiography professionals, a summary by the Society of Radiographers AI working group. *Radiography* 2021;**27**(4):1192–202. https://doi.org/10.1016/j.radi.2021.07.028.
5. Zhong J, Ho R, Gourtsoyianni S, Oleaga L, Catalano C, Becker M, et al. Attracting the next generation of radiologists: a statement by the European Society of Radiology (ESR). *Insights Imaging* 2022;**13**(1):84. https://doi.org/10.1186/s13244-022-01221-8.
6. Tajmir SH, Alkasab TK. Toward augmented radiologists. *Acad Radiol* 2018;**25**(6):747–50. https://doi.org/10.1016/j.acra.2018.03.007.
7. Huisman M, Ranschaert E, Parker W, Mastrodicasa D, Koci M, Pinto de Santos D, et al. An international survey on AI in radiology in 1,041 radiologists and radiology residents part 1: fear of replacement, knowledge, and attitude. *Eur Radiol* 2021;**31**(9):7058–66. https://doi.org/10.1007/s00330-021-07781-5.
8. Wang C, Xie H, Wang S, Yang S, Hu L. Radiological education in the era of artificial intelligence: a review. *Medicine* 2023;**102**(1):e32518. https://doi.org/10.1097/MD.0000000000032518.
9. Gorospe-Sarasúa L, Muñoz-Olmedo JM, Sendra-Portero F, de Luis-García R. Challenges of Radiology education in the era of artificial intelligence. *Radiología (English Edition)* 2022;**64**(1):54–9. https://doi.org/10.1016/j.rxeng.2020.10.012.
10. Ooi S, Makmur A, Soon Y, Fook-Chong S, Liew C, Sia D, et al. Attitudes toward artificial intelligence in radiology with learner needs assessment within radiology residency programmes: a national multi-programme survey. *Singap Med J* 2021;**62**(3):126–34. https://doi.org/10.11622/smedj.2019141.
11. Lewis SJ, Gandomkar Z, Brennan PC. Artificial Intelligence in medical imaging practice: looking to the future. *J Med Radiat Sci* 2019;**66**(4):292–5. https://doi.org/10.1002/jmrs.369.
12. Kim JH, Kim JY, Kim GH, Kang D, Kim IJ, Seo J, et al. Clinical validation of a deep learning algorithm for detection of pneumonia on chest radiographs in emergency department patients with acute febrile respiratory illness. *J Clin Med* 2020;**9**(6):1–11. https://doi.org/10.3390/jcm9061981.

13. Hwang EJ, Park S, Jin KN, Kim JI, Choi SY, Lee JH, et al. Development and validation of a deep learning–based automatic detection algorithm for active pulmonary tuberculosis on chest radiographs. *Clin Infect Dis* 2019;**69**(5):739–47. https://doi.org/10.1093/cid/ciy967.
14. Nam JG, Park S, Hwang EJ, Lee JH, Jin KN, Lim KY, et al. Development and validation of deep learning–based automatic detection algorithm for malignant pulmonary nodules on chest radiographs. *Radiology* 2019;**290**(1):218–28. https://doi.org/10.1148/radiol.2018180237.
15. Hwang EJ, Nam JG, Lim WH, Park SJ, Jeong YS, Kang JH, et al. Deep learning for chest radiograph diagnosis in the emergency department. *Radiology* 2019;**293**(3):573–80. https://doi.org/10.1148/radiol.2019191225.
16. Seah JCY, Tang CHM, Buchlak QD, Holt XG, Wardman JB, Aimoldin A, et al. Effect of a comprehensive deep-learning model on the accuracy of chest x-ray interpretation by radiologists: a retrospective, multireader multicase study. *Lancet Digit Health* 2021;**3**(8):e496–506. https://doi.org/10.1016/S2589-7500(21)00106-0.
17. Lång K, Josefsson V, Larsson AM, Larsson S, Högberg C, Sartor H, et al. Artificial intelligence-supported screen reading versus standard double reading in the Mammography Screening with Artificial Intelligence trial (MASAI): a clinical safety analysis of a randomised, controlled, non-inferiority, single-blinded, screening accuracy study. *Lancet Oncol* 2023;**24**(8):936–44. https://doi.org/10.1016/S1470-2045(23)00298-X.
18. Lakhani P, Sundaram B. Deep learning at chest radiography: automated classification of pulmonary tuberculosis by using convolutional neural networks. *Radiology* 2017;**284**(2):574–82. https://doi.org/10.1148/radiol.2017162326.
19. Sahiner B, Pezeshk A, Hadjiiski LM, Wang X, Drukker K, Cha KH, et al. Deep learning in medical imaging and radiation therapy. *Med Phys* 2019;**46**(1):e1–36. https://doi.org/10.1002/mp.13264.
20. Forney MC, McBride AF. Artificial intelligence in radiology residency training. *Semin Muscoskel Radiol* 2020;**24**(1):74–80. https://doi.org/10.1055/s-0039-3400270.
21. Huisman M, Ranschaert E, Parker W, Mastrodicasa D, Koci M, Pinto de Santos D, et al. An international survey on AI in radiology in 1041 radiologists and radiology residents part 2: expectations, hurdles to implementation, and education. *Eur Radiol* 2021;**31**(11):8797–806. https://doi.org/10.1007/s00330-021-07782-4.
22. Santomartino SM, Siegel E, Yi PH. Academic radiology departments should lead artificial intelligence initiatives. *Acad Radiol* 2023;**30**(5):971–4. https://doi.org/10.1016/j.acra.2022.07.011.
23. Hashmi OU, Chan N, de Vries CF, Gangi A, Jehanli L, Lip G. Artificial intelligence in radiology: trainees want more. *Clin Radiol* 2023;**78**(4):e336–41. https://doi.org/10.1016/j.crad.2022.12.017.
24. Rainey C, O'Regan T, Matthew J, Skelton E, Woznitza N, Chu KY, et al. Beauty is in the AI of the beholder: are we ready for the clinical integration of artificial intelligence in radiography? An exploratory analysis of perceived AI knowledge, skills, confidence, and education perspectives of UK radiographers. *Front Digit Health* 2021;**3**. https://doi.org/10.3389/fdgth.2021.739327.
25. Schuur F, Rezazade Mehrizi MH, Ranschaert E. Training opportunities of artificial intelligence (AI) in radiology: a systematic review. *Eur Radiol* 2021;**31**(8):6021–9. https://doi.org/10.1007/s00330-020-07621-y.
26. Ngo B, Nguyen D, vanSonnenberg E. The cases for and against artificial intelligence in the medical school curriculum. *Radiol Artif Intell* 2022;**4**(5). https://doi.org/10.1148/ryai.220074.
27. Health Education England. *Preparing the healthcare workforce to deliver the digital future the Topol Review an independent report on behalf of the Secretary of State for Health and Social Care*. 2019.
28. Health and Care Professions Council. *The standards of proficiency for radiographers* [Internet]. 2023 [cited 2023 Sep 1]; Available from: https://www.hcpc-uk.org/standards/standards-of-proficiency/radiographers/.
29. Department of Health and Social Care. *£21 million to roll out artificial intelligence across the NHS* [Internet]. GOV.UK. 2023 [cited 2023 Jul 1];Available from: https://www.gov.uk/government/news/21-million-to-roll-out-artificial-intelligence-across-the-nhs.
30. Doherty G, McLaughlin L, Rainey C, Hughes C, Bond R, McConnell J, et al. Radiographer/radiologist education and learning in artificial intelligence (REAL-AI) [Internet]. In: *United Kingdom imaging and oncology congress*; 2023 [cited 2023 Jul 1]. Available from: https://www.ukio.org.uk/wp-live/wp-content/uploads/2023/07/Abstracts-Book-2023.pdf.
31. Gowda V, Jordan SG, Awan OA. Artificial intelligence in radiology education: a longitudinal approach. *Acad Radiol* 2022;**29**(5):788–90. https://doi.org/10.1016/j.acra.2021.08.022.
32. Velez-Florez MC, Ghosh A, Patton D, Sze R, Reid JR, Sotardi S. Artificial intelligence curriculum needs assessment for a pediatric radiology fellowship program: what, how, and why? *Acad Radiol* 2023;**30**(2):349–58. https://doi.org/10.1016/j.acra.2022.04.026.
33. Dumić-Čule I, Orešković T, Brkljačić B, Kujundžić Tiljak M, Orešković S. The importance of introducing artificial intelligence to the medical curriculum – assessing practitioners' perspectives. *Croat Med J* 2020;**61**(5):457–64. https://doi.org/10.3325/cmj.2020.61.457.
34. Li MD, Little BP. Appropriate reliance on artificial intelligence in radiology education. *J Am Coll Radiol* 2023;**20**(11):1126–30. https://doi.org/10.1016/j.jacr.2023.04.019.
35. Buçinca Z, Malaya MB, Gajos KZ. To Trust or to Think: cognitive forcing functions can reduce over-reliance on AI in AI-assisted decision-making. *Proc ACM Hum Comput Interact* 2021;**5**(CSCW1):1–21. https://doi.org/10.1145/3449287.
36. Charow R, Jeyakumar T, Younus S, Dolatabadi E, Salhia M, Al-Mouaswas D, et al. Artificial intelligence education programs for Health care professionals: scoping review. *JMIR Med Educ* 2021;**7**(4):e31043. https://doi.org/10.2196/31043.
37. Long D, Magerko B. What is AI literacy? Competencies and design considerations. In: *Proceedings of the 2020 CHI conference on human factors in computing systems*. New York, NY, USA: ACM; 2020. p. 1–16. https://doi.org/10.1145/3313831.3376727.
38. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. *Int J Soc Res Methodol* 2005;**8**(1):19–32. https://doi.org/10.1080/1364557032000119616.
39. Lindqwister AL, Hassanpour S, Lewis PJ, Sin JM. AI-RADS: an artificial intelligence curriculum for residents. *Acad Radiol* 2021;**28**(12):1810–6. https://doi.org/10.1016/j.acra.2020.09.017.
40. Perchik JD, Smith AD, Elkassem AA, Park JM, Rothenberg SA, Tanwar M, et al. Artificial intelligence literacy: developing a multi-institutional infrastructure for AI education. *Acad Radiol* 2023;**30**(7):1472–80. https://doi.org/10.1016/j.acra.2022.10.002.
41. Hedderich DM, Keicher M, Wiestler B, Gruber MJ, Burwinkel H, Hinterwimmer F, et al. AI for doctors—a course to educate medical professionals in artificial intelligence for medical imaging. *Healthcare* 2021;**9**(10):1278. https://doi.org/10.3390/healthcare9101278.
42. Laupichler MC, Hadizadeh DR, Wintergerst MWM, von der Emde L, Paech D, Dick EA, et al. Effect of a flipped classroom course to foster medical students' AI literacy with a focus on medical imaging: a single group pre-and post-test study. *BMC Med Educ* 2022;**22**(1):803. https://doi.org/10.1186/s12909-022-03866-x.
43. van de Venter R, Skelton E, Matthew J, Woznitza N, Tarroni G, Hirani SP, et al. Artificial intelligence education for radiographers, an evaluation of a UK postgraduate educational intervention using participatory action research: a pilot study. *Insights Imaging* 2023;**14**(1):25. https://doi.org/10.1186/s13244-023-01372-2.
44. World Health Organization. *Advice for the public on covid-19* [Internet]. WHO.INT; 2019 [cited 2023 Jul 1];Available from: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public.
45. Bishop J, Verleger M. The flipped classroom: a survey of the research [Internet]. In: *2013 ASEE annual conference & exposition proceedings. ASEE conferences*; 2013. 23.1200.1-23.1200.18.Available from: http://peer.asee.org/22585.
46. Al-Samarraie H, Shamsuddin A, Alzahrani AI. A flipped classroom model in higher education: a review of the evidence across disciplines. *Educ Technol Res Dev* 2020;**68**(3):1017–51. https://doi.org/10.1007/s11423-019-09718-8.
47. Tomesko J, Cohen D, Bridenbaugh J. Using a virtual flipped classroom model to promote critical thinking in online graduate courses in the United States: a case presentation. *J Educ Eval Health Prof* 2022;**19**:5. https://doi.org/10.3352/jeehp.2022.19.5.
48. Long T, Cummins J, Waugh M. Use of the flipped classroom instructional model in higher education: instructors' perspectives. *J Comput High Educ* 2017;**29**(2):179–200. https://doi.org/10.1007/s12528-016-9119-8.
49. Aristovnik A, Keržič D, Ravšelj D, Tomaževič N, Umek L. Impacts of the COVID-19 pandemic on life of higher education students: a global perspective. *Sustainability* 2020;**12**(20):8438. https://doi.org/10.3390/su12208438.
50. Dost S, Hossain A, Shehab M, Abdelwahed A, Al-Nusair L. Perceptions of medical students towards online teaching during the COVID-19 pandemic: a national cross-sectional survey of 2721 UK medical students. *BMJ Open* 2020;**10**(11):e042378. https://doi.org/10.1136/bmjopen-2020-042378.
51. Grant K, Gedeon S. The impact of COVID-19 on university teaching. In: *The university of the future-responding to COVID-19*; 2020. p. 161.
52. Cranfield DJ, Tick A, Venter IM, Blignaut RJ, Renaud K. Higher education students' perceptions of online learning during COVID-19—a comparative study. *Educ Sci* 2021;**11**(8):403. https://doi.org/10.3390/educsci11080403.