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UK reporting radiographers' perceptions of AI in radiographic image interpretation – Current perspectives and future developments

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ABSTRACT

Introduction: Radiographer reporting is accepted practice in the UK. With a national shortage of radiographers and radiologists, artificial intelligence (AI) support in reporting may help minimise the backlog of unreported images. Modern AI is not well understood by human end-users. This may have ethical implications and impact human trust in these systems, due to over- and under-reliance. This study investigates the perceptions of reporting radiographers about AI, gathers information to explain how they may interact with AI in future and identifies features perceived as necessary for appropriate trust in these systems.
Methods: A Qualtrics® survey was designed and piloted by a team of UK AI expert radiographers. This paper reports the third part of the survey, open to reporting radiographers only.
Results: 86 responses were received. Respondents were confident in how an AI reached its decision (n = 53, 62%). Less than a third of respondents would be confident communicating the AI decision to stakeholders. Affirmation from AI would improve confidence (n = 49, 57%) and disagreement would make respondents seek a second opinion (n = 60, 70%). There is a moderate trust level in AI for image interpretation. System performance data and AI visual explanations would increase trust.
Conclusions: Responses indicate that AI will have a strong impact on reporting radiographers' decision making in the future. Respondents are confident in how an AI makes decisions but less confident explaining this to others. Trust levels could be improved with explainable AI solutions.
Implications for practice: This survey clarifies UK reporting radiographers' perceptions of AI, used for image interpretation, highlighting key issues with AI integration.

Introduction and background

The NHS is under significant pressure from increasing service demand and decreasing staffing levels. This is particularly true in diagnostic radiology where staffing levels are not increasing in parallel to service demand.[1] Many clinicians are already experiencing burn out and fatigue, which may become more problematic in the post pandemic healthcare setting.[1–3]

Radiographer reporting

Radiographer reporting allows for timely reporting of images with a high accuracy at decreased cost.[4–6] The Getting It Right First

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Time (GIRFT) report recommends training more reporting radiographers and using AI to support some aspects of image interpretation in the future.[7] This is echoed in 'Diagnostics: Recovery and Renewal' (2020)[3] which recommends that a minimum of 50% of plain radiographic images should be reported by a radiographer. However, with an average radiographer vacancy rate of 10.5% in the UK,[8] the report recognises that this aim will require the training and recruitment of an additional 4000 radiographers. The NHS, in its Long-Term Plan also promotes the role AI and advanced technologies could play in the future of healthcare.[9] Computers have been used in image interpretation for many years, however new systems using advanced technologies are now more prevalent clinically, enabling improved performance with reduced false positive rates compared with earlier human programmed machines.[10,11] However, the complexity of these systems mean that the system processes are not transparent, sometimes even to the developer.[12,13]

Computer vision

A paradigm shift in computer vision occurred in 2012 when a convolutional neural network (CNN) won the ImageNet challenge for identification of common objects, far outperforming its next nearest competitor.[14] The use of complex AI models, such as CNNs, in medical imaging presents several unique challenges, such as the lack of transparency in how the system reaches its decisions. To counteract this, there have been attempts to explain the way in which these systems reach their diagnosis, such as the use of heatmaps, overall system performance, region of interest identification, and confidence in prediction for a particular image.[15–19] The format of end-user interfaces is particularly important for radiographers and radiologists. There is a reasonable expectation that when AI is implemented into care pathways in radiology, the systems can support greater interaction between the clinical reporter and patient at the time and point of care.[20]

Barriers to successful implementation of AI in image interpretation

There are several potential barriers to the effective implementation of AI systems, including clinical practitioners' trust, system operating knowledge, ethical issues and integration of the AI into existing infrastructure.[21–26] As technology translates from concept into a clinically useful product, it is important to recognize and address the concerns and opinions of end users of these systems, as central to the successful adoption and implementation of these technologies. There has been increasing focus on involving clinicians in the development of AI systems as 'domain experts' to ensure clinical relevance and usefulness.[27,28] The perceptions of clinical end-users about AI should be understood before AI comes into widespread use.

Adequate levels of trust and awareness of potential automation bias are some areas which are being discussed as central to AI adoption in the literature.[29–31] The clinician, as the end-user should be able to interact effectively with the AI whilst exercising due caution. Methods to interpret and explain the functionality of the AI have been proposed to mitigate against either over- or under-reliance on the system.[15,32,33] Interpretable AI refers to the understanding of the system itself therefore allowing the end-user to understand the mechanics behind its decision making.[17] This can be difficult in modern AI where some of the mathematical and statistical processing is unintelligible, even to the developer. Explainable AI refers to methods whereby the user can be provided with an indication of how the system reached its decision in a human-comprehensible way, for instance, by a colour-coded overlay of decision confidence levels on a radiographic image.[15]

Impact of AI on clinicians' decision making

Studies on the use of clinical decision support tools in different fields of health care have found that a user's response to the information gained from the AI may differ. This depends on several factors, such as the experience level of the user and the complexity of the task.[31,32] Excessive trust, decreased levels of experience and increased complexity of a task have been shown to increase the likelihood of the clinician changing their mind from their initial decision to agree with the AI.[29–31] Whilst studies are reporting impressive and even human-exceeding performances of AI-enabled tools when used in image interpretation tasks,[34,35] no system in use or development is flawless. Incorrect automated diagnoses have been shown to negatively impact the decision making of expert and non-expert clinicians alike.[31] It is therefore important to ensure all clinicians exercise appropriate caution and own judgement and use AI to assist and augment, but not to solely guide decision making.[30,32]

Rationale and aims

This survey aims to provide insight into the current use of AI in image interpretation by reporting radiographers in the UK and to identify how they currently interact, or expect they will interact, with this technology, in the future

Methodology

Questionnaire design and recruitment of participants

A Qualtrics® survey was designed, based on the available literature and with input from the Society of Radiographers (SoR) AI Working Group, incorporating themes from the SoR AI Guidance Document for Clinical Imaging and Radiotherapy.[36] The design and reporting of the survey was based on the Checklist for Reporting Results of Internet E-Surveys (CHERRIES).[37] Ethical permission was gained from City, University of London Research Ethics Committee (ETH1920-1989). The entire survey was open to all UK radiographers, although the sub-section reported here was open to reporting radiographers only.

The survey link was distributed on professional social media (LinkedIn®/Twitter®) and via authors' professional networks. It was available from the 12th February to 6th April 2021.

The survey instrument

There were eight questions in this part of the survey, focussed specifically on AI as used in radiographer reporting. There were different question types offered: multiple choice, Likert scale and some free text options.

Validity and reliability of the survey instrument

The survey was piloted on 12 radiographers with differing professional backgrounds (including reporting) with a range of years' experience. Feedback was sought on the relevance of the survey contents, readability, and technical aspects of the survey design, therefore ensuring face and content validity.

Post-hoc Cronbach's alpha was calculated to ensure internal consistency on the Likert scale questions ($\alpha = 0.869$).

Data analysis

Data analysis was conducted on IBM SPSS® (version 23). Results are reported using descriptive statistics. Statistical analyses were conducted to investigate any correlations between variables. Data was gathered on the perceptions of individuals and therefore considered to be either ordinal or nominal only. Non-parametric tests were therefore used for the purposed of analysis. Spearman's rho and Kendall's tau were used to investigate any relationship between ordinal data. Chi square likelihood ratio was used to investigate correlations in nominal data, as the data violated assumptions necessary for Pearson's Chi square test to be used.

Results are represented graphically in percentages for questions where the participant was only permitted to select one response and in counts, where multiple responses were possible. Weightings were not applied to any questions. Error bars are included to represent the standard error of proportion.

Results

There were 411 full survey responses after removal of blank surveys and surveys which respondents did not give consent to data analysis. Incomplete surveys were included in the analysis to contribute to the final results and as an acknowledgement that not all reporting radiographers would be in position to answer all of the questions due to varying personal and professional experiences.

Demographic information

Full details of respondents' demographic information are given in Table 1. Representation from each profession was broadly proportional to the UK radiographer population (diagnostic radiography (DR): therapeutic radiography (TR); 4:1).[38]

Statistical analyses

Independent variables of years' of clinical experience, level of highest academic qualification and current use of AI in reporting practice were compared to dependent variables given in the paragraphs below. Spearman's rho or Kendall's tau (ordinal data) and Chi square Likelihood ratio (nominal data) were used to investigate any relationships. No correlations were found between any variable tested.

Image reporting and use of AI as part of respondents' clinical role

This section of the survey was open to DR only. Of the total respondents, 86 indicated that image reporting was a part of their role; this is a representative sample as it is more than the reporting radiographers currently registered with the Society and College of Radiographers (SCoR) respective specialist interest group (n = 70), although it is acknowledged that some reporting radiographers are not registered with SCoR. If not a reporting radiographer, respondents exited the survey. Of the remaining respondents, only 10.5% (n = 9) were currently using AI as part of their reporting role.

Understanding of how an AI system reaches its decision

Reporting radiographer respondents were asked if they understood how an AI makes its decisions. 61.6% (n = 53) of respondents agreed by selecting any of the 'agree' options ('aggregate agreement'), and 29.1% (n = 25) selecting any of the 'disagree' options ('aggregate disagreement'). The most popular selection was the 'somewhat agree' option (n = 34, 39.5%) (Fig. 1).

Respondents' confidence in explaining AI decisions

The majority of respondent disagreed that they would be confident in explaining the AI decision to other healthcare practitioners (59.3% (n = 51) aggregate disagreement; 27.9% (n = 24) aggregate agreement). Similarly, only 29.1% agreed that they would be confident explaining AI decisions to patients and carers (n = 25). No respondents indicated strong agreement with either statement (Fig. 2).

Impact of AI on diagnosis/professional opinion

Respondents indicated that an affirmation from AI would serve to increase their certainty in their diagnosis (n = 49, 57%), while disagreement from an AI system would cause them to feel less certainty (n = 29, 33.7%). A large proportion of respondents stated they would seek a second opinion when AI disagrees with them (n = 60, 69.8%) (Fig. 3).

Factors influencing trustworthiness of AI in image interpretation decision support

Respondents were asked to indicate their trust in AI for diagnostic image interpretation decision support on a 0–10 scale (0 = no trust and 10 = absolute trust), resulting in a mode of 5, mean of 5.28 and median of 5 (Fig. 4).

Additionally, respondents were asked to choose from a list of suggestions of features to increase their trust in a clinical AI system. Respondents could select all applicable options (Fig. 5). An indication of the 'overall performance/accuracy of the system', 'visual explanation' and 'indication of the confidence of the system in its diagnosis' were the most popular choices. One respondent made an additional suggestion using the 'other' option:

'I would want to know that the system would be equally accurate in dismissing insignificant findings and not generating additional work'.

The other two respondents who inputted text using the 'other' function did not add any suggestions:

'Do not understand'.

'Unsure'.

Discussion

Image reporting

Many respondents (n = 77, 89.5%) indicated that they were not utilising AI as part of their reporting role. However, an international technography study found that 70% of AI applications were focused on 'Perception and Reasoning', including feature extraction, diagnosis and highlighting of specific features.[11] This slow pick up of AI in reporting and image interpretation might relate with the multitude of challenges for AI adoption, as described in introduction, and the lack of reliable evidence on AI-enabled system accuracy and performance from prospective studies. With shortages of both radiologists and radiographers,[1,8] the impact of the COVID-19 pandemic on imaging services and staffing levels[39,40] and the aspirations of the NHS long Term plan,[9] there will be more scope for the integration of these systems to assist with diagnostic imaging decision making. This demand, coupled with the availability and relative simplicity of plain radiographic images may mean that this area will be targeted for continued development of AI systems.[10] International consensus among radiologists is that AI will aid diagnostic accuracy, with systems acting as a second reader.[24,41,42] Reporting radiographer respondents, in contrast, feel that interpretation should remain a mainly human task; perhaps influenced by their professional background of values-based radiography[43] and humanistic models of care assuring that care is tailored to the person during the acquisition of images.[23,44]

Table 1
Respondents' demographic details.

		Diagnostic radiography	Therapeutic radiography
Region of UK where respondents currently work/%	England	56.7 (n = 183)	88.2 (n = 67)
	Scotland	30 (n = 97)	9.2 (n = 7)
	Wales	1.9 (n = 6)	1.3 (n = 1)
	Northern Ireland	11.1 (n = 36)	1.3 (n = 1)
	Channel Islands	0.3 (n = 1)	0 (n = 0)
Years practicing radiography/%	0–2 years	22.7 (n = 75)	23.4 (n = 18)
	3–5 years	10.6 (n = 35)	16.9 (n = 13)
	6–10 years	13.9 (n = 46)	11.7 (n = 9)
	11–20 years	23.0 (n = 76)	23.4 (n = 18)
	>20 years	27.5 (n = 91)	22.1 (n = 17)
	Not practicing	1.2 (n = 4)	1.3 (n = 1)
	Retired	1.3 (n = 4)	1.3 (n = 1)
Age range/%	18–25 years old	19.3 (n = 63)	23.7 (n = 18)
	26–35 years old	28.4 (n = 93)	26.3 (n = 20)
	36–45 years old	27.2 (n = 89)	25.0 (n = 19)
	46–55 years old	12.5 (n = 41)	18.4 (n = 14)
	56–65 years old	11.3 (n = 37)	6.6 (n = 5)
	>65 years old	1.2 (n = 4)	0 (n = 0)
Highest academic qualification/%	A-level	14.9 (n = 48)	11.8 (n = 9)
	BSc	24.2 (n = 78)	35.5 (n = 27)
	PgCert	19.9 (n = 64)	1.3 (n = 1)
	PgDip	13.0 (n = 42)	6.6 (n = 5)
	MSc	19.6 (n = 63)	36.8 (n = 28)
	PhD/EdD/DProf or equivalent	1.9 (n = 6)	3.9 (n = 3)
	Other	6.5 (n = 21)	3.9 (n = 3)
Clinical setting/counts *(respondents were permitted more than one selection)*	University teaching hospital	n = 195	n = 50
	District general hospital	n = 103	n = 19
	Private sector	n = 12	n = 2
	Poly-trauma unit	n = 30	n = 0
	Mobile unit	n = 4	n = 0
	Other	n = 14	n = 5
	I do not work in the clinical setting	n = 25	n = 4
Current role/%	Assistant practitioner radiographer	1.2 (n = 4)	0 (n = 0)
	Undergraduate radiography student	19.6 (n = 63)	13.2 (n = 10)
	Clinical radiographer	39.1 (n = 126)	38.2 (n = 29)
	Research radiographer	0.9 (n = 3)	2.6 (n = 2)
	Advanced practitioner	15.8 (n = 51)	17.1 (n = 13)
	PhD researcher radiographer	0.6 (n = 2)	0 (n = 0)
	Other	3.1 (n = 10)	6.6 (n = 5)
	Academic in radiography: teaching only	0.9 (n = 3)	1.3 (n = 1)
	Industry partner	0.3 (n = 1)	1 (n = 0)
	Consultant radiographer	4.3 (n = 14)	13.2 (n = 10)
	Clinical academic/lecturer:practitioner	3.1 (n = 10)	1.3 (n = 1)
	Radiology/Radiographer/radiotherapy manager	6.2 (n = 20)	6.6 (n = 5)
	Retired radiographer	0.9 (n = 3)	0 (n = 0)
	Academic in radiography: teaching and research	3.7 (n = 12)	0 (n = 0)
Diagnostic radiography Sub-specialism/counts *(respondents were permitted more than one selection)*	General radiography inc. emergency, theatre and fluoroscopy	n = 207	
	Mammography	n = 32	
	MRI	n = 56	
	CT	n = 100	
	Ultrasound	n = 25	
	Interventional	n = 44	
	PET/CT	n = 3	
	PET/MRI	n = 1	
	DEXA/DXA	n = 5	
	Reporting	n = 63	
	Radiology manager	n = 20	
	PACS administrator	n = 9	
	Education	n = 54	
	Policy maker/professional advocate	n = 11	
	Other (diagnostic)	n = 22	
Therapeutic radiography Sub-specialism/counts *(respondents were permitted more than one selection)*	Pre-treatment, simulation, contouring, immobilisation		n = 35
	Treatment planning		n = 15
	Treatment delivery		n = 54
	Patient information/support/review		n = 23
	Educator		n = 7
	Research		n = 7
	Management		n = 10
	Quality assurance/Quality improvement		n = 7
	DEXA/DXA clinical applications		n = 0
	Other (therapeutic)		n = 7

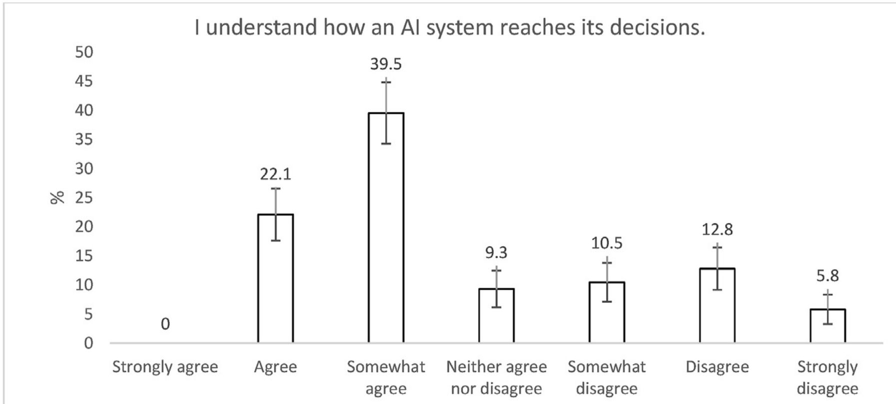

Figure 1. 'I understand how an AI system reaches its decisions' (n = 86) (Error bars represent the standard error of proportion).

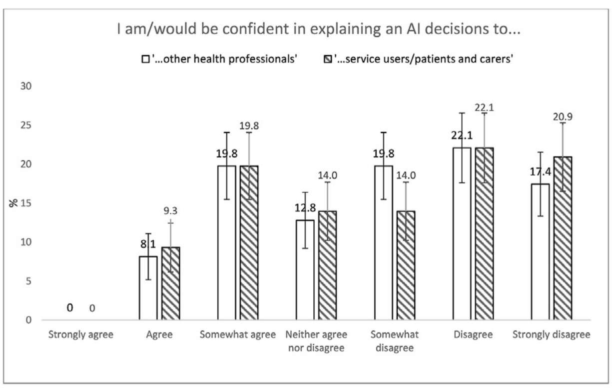

Figure 2. 'I would be confident in explaining AI decisions to ' … other health professionals' and ' … service users and carers' (n = 86) (Error bars represent the standard error of proportion).

Understanding of how an AI system reaches its decision

The level of clinicians' understanding of AI warrants further investigation. Studies report that radiographers perceive they have little confidence in modern AI terminology and feel they have no skill in clinical AI.[45–47] It should be noted, however, that 'confidence' is a subjective feeling rather than indication of the likelihood of the decision being correct[48] i.e. confidence may not be an indicator of competence.[49,50] Many respondents to this study indicate understanding in how AI makes its decisions (n = 53, 61.6%). This may be due to participants to this section of the survey having higher levels of academic achievement; a correlation found in the first part of this survey.[47] These conflicting reports paint a confusing picture, and any lack of understanding may act as a barrier to implementation and use of AI in clinical departments.[23] The contextual nature of results will persist for as long as AI implementation in medical imaging is heterogenous between different sectors, modalities and functions.[51]

Confidence in explaining AI decisions

Despite indicating understanding of AI, less than 30.0% of the respondents felt that they would be confident in explaining AI decisions to healthcare professionals or patients/carers. Understanding how the AI made its decision may make it easier for the clinician to explain the decision to others, although there is need for balance as more transparent models generally exhibit poorer performance, due to decreased complexity.[32,52]

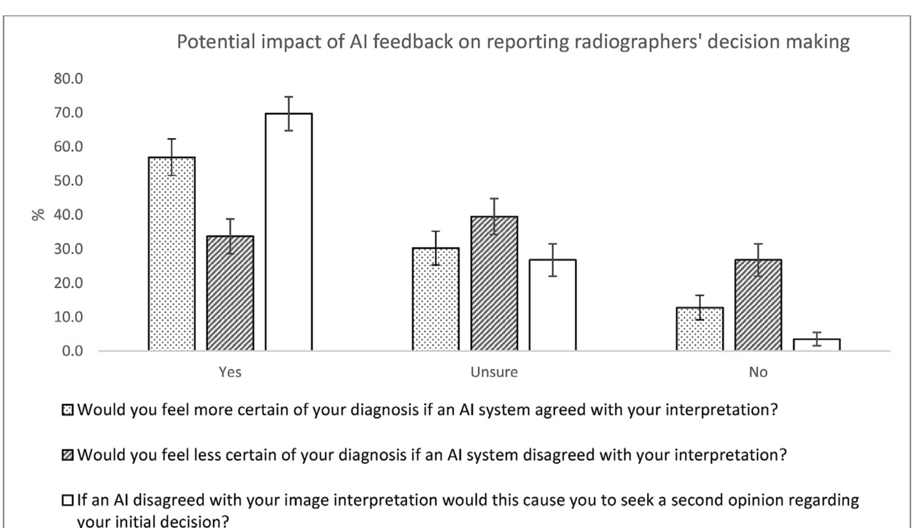

Figure 3. Potential impact of AI feedback on reporting radiographers' decision making (n = 86)(Error bars represent the standard error of proportion).

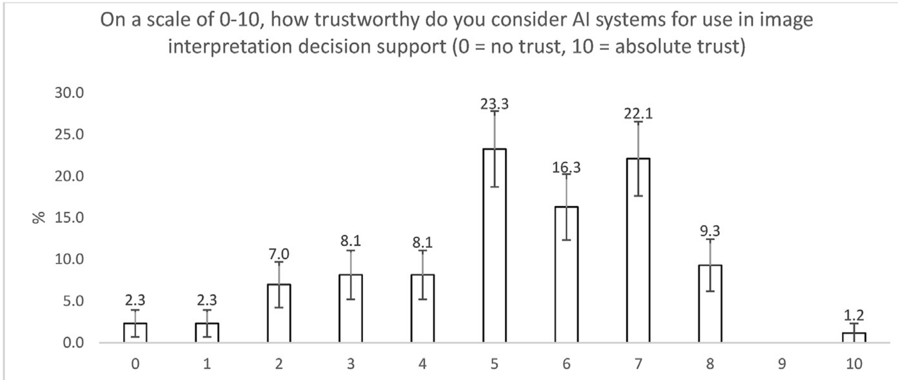

Figure 4. On a scale of 0–10, how trustworthy do you consider AI systems for use in *image interpretation decision support* (0 = no trust, 10 = absolute trust) (n = 86) (Error bars represent the standard error of proportion).

Impact of AI on diagnosis/professional opinion

It is imperative to understand how AI will impact human decision making in order to assure users of the safe deployment of systems. Automation Bias (AB) is a potential risk which occurs when over-reliance on a decision support tool causes the user to change their mind from a correct to an incorrect diagnosis. Bond et al. (2018)[31] and Goddard et al. (2014)[30] report the impact of AB in relation to the experience level of clinicians using AI in ECG reading and prescribing amongst physicians, respectively and found that more experienced clinicians are less likely to change their mind from their initial decision, but are equally susceptible to AB. In this study, respondents indicated that an agreement from an AI system would increase their certainty in their interpretation (n = 49, 57.0%), while disagreement from an AI would cause them to seek a second opinion (n = 60, 69.8%).

We might expect that these are conservative findings as the evidence in the literature indicates that reporting radiographers, as experienced clinicians, are less likely than clinicians with less experience to change their mind.

Factors influencing trustworthiness of AI in image interpretation decision support

Lack of trust has been cited as a potential barrier to the implementation of AI in the clinical setting,[28,33,53] although excessive trust may also lead to an increased likelihood of the clinician changing their mind from their initial decision.[30] Adequate trust levels are needed to ensure beneficial use and management of expectations of end-users. The respondents to this survey reported a mean trust of five out of ten, indicating neither a lack of, nor excessive trust. This is in contrast to a study examining attitudes of radiologists, IT specialists and industry to AI, where only a quarter of respondents felt that they could trust results from an AI system[53] but this might relate to interpretation of more complex images, like those from cross-sectional imaging (MRI and CT).

Respondents to this survey were asked which features of an AI system may offer assurance of trustworthiness. The most popular choices were ‘indication of the overall performance of the system’ (n = 76), and ‘visual explanation’ (n = 67). Two main methods to increase trust in AI have been proposed in the literature – (i) model explainability and (ii) interpretability. Explainability refers to ‘human-comprehensible’ methods to reveal how the decision was reached while interpretability is the knowledge of the user into how the system works.[17] Interpretability of modern AI systems can be difficult, due to system complexity.[13,15] Visual explanations, e.g. colour-coded overlays, have been proposed as means to explain the focus of the system in making its decision,[15,16] the desire for which has been supported by the responses to this survey. However, caution is recommended with the use of explainable AI – if the prediction can be incorrect, the explanation can be incorrect, leading to overinflated trust in the system.[19] Explainability skeptics

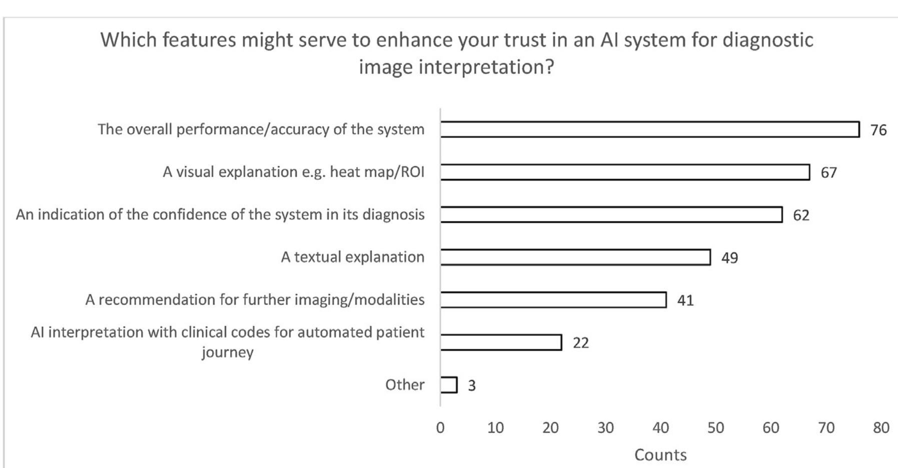

Figure 5. Which features might serve to enhance your trust in an AI system for diagnostic image interpretation? (multiple responses permitted per respondent).

argue that the performance of the system may be sufficient to gain end-users' trust.[33,54] Respondents to this survey may agree with this sentiment, indicating that they would have greatest desire for the overall performance data to be supplied. However, performance indicators may be biased too, as human errors might creep into these indicators as well depending on what is the reference level for these measurements.

Limitations

The respondents to this survey were recruited via convenience sampling and therefore may not be a true reflection of the UK radiographer population. This sampling method has been used in other comparable studies in this area, with which comparisons are made[44,46] (Abuzaid et al., 2020; Ryan et al., 2021).

There are currently 70 SoR members enrolled to use an online networking space for reporting radiographers, although estimates bring the number of reporting radiographers to be much higher, with 264 UK reporting radiographers responding to a survey by Milner et al. (2016).[55] There were 86 reporting radiographers responding to this section of the survey. The results may therefore not be representative of the target population as a whole, however with the lack of definitive data on the number of practicing reporting radiographers in the UK this is difficult to determine.

Further investigation is required to quantify automation bias and trust in radiographers of all experience levels to provide targeted intervention suggestions. Focus groups or interviews may allow for richer perception data to be obtained with an inductive approach.

The survey questions were developed by a team of UK radiography AI experts to elicit specific information pertinent to the focus of this study. A validated scale did not exist in the literature to best capture the perceptions of the target population.

Conclusions

While many reporting radiographers are not currently using AI as part of their reporting role, this may change in the near future. Radiographers responding to this survey are confident in understanding how an AI system reached its decisions but less confident in explaining the process to patients and other healthcare staff. This may illustrate that confidence does not equate to competence and therefore education of the workforce and increased transparency of the systems are suggested. As the use of AI becomes more prevalent, consideration should be given to the expectations of patients and service users in the role of AI in radiographic image interpretation.

Developers should engage with clinicians to ensure they have the information they need to allow for appropriate trust to be built. Awareness of how clinicians interact with an AI system may promote responsible use of clinically useful AI in the future.

Conflict of interest statement

None.

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