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User-centric eXplainable AI criteria for implementing AI-based denoising in PET/CT

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A B S T R A C T

Introduction: The clinical adoption of AI-based denoising in PET/CT relies on the development of transparent and trustworthy tools that align with the radiographers' needs and support integration into routine practice. This study aims to determine the key characteristics of an eXplainable Artificial Intelligence (XAI)/tool aligning the radiographers' needs to facilitate the clinical adoption of AI-based denoising algorithm in PET/CT.
Methods: Two focus groups were organised, involving ten voluntary participants recruited from nuclear medicine departments from Western-Switzerland, forming a convenience sample of radiographers. Two different scenarios, matching or mismatching the ground truth were used to identify their needs and the questions they would like to ask to understand the AI-denoising algorithm. Additionally, the characteristics that an XAI tool should possess to best meet their needs were investigated. Content analysis was performed following the three steps outlined by Wanlin. Ethics cleared the study.
Results: Ten radiographers (aged 31-60y) identified two levels of explanation: (1) simple, global explanations with numerical confidence levels for rapid understanding in routine settings; (2) detailed, case-specific explanations using mixed formats where necessary, depending on the clinical situation and users to build confidence and support decision-making. Key questions include the functions of the algorithm ('what'), the clinical context ('when') and the dependency of the results ('how'). An effective XAI tool should be easy, adaptable, user-friendly and not disruptive to workflows.
Conclusion: Radiographers need two levels of explanation from XAI tools: global summaries that preserve workflow efficiency and detailed, case-specific insights when needed. Meeting these needs is key to fostering trust, understanding, and integration of AI-based denoising in PET/CT.
Implications for practice: Implementing adaptive XAI tools tailored to radiographers' needs can support clinical workflows and accelerate the adoption of AI in PET/CT imaging.

Introduction

The integration of artificial intelligence (AI) in medical imaging (MI) applications, such as those for patient diagnosis, treatment decisions, and workflow management, holds great potential for improving patient outcomes and operational efficiency.[1,2] *However, these advances raise important ethical concerns that must be carefully examined. The question of responsibility is central, as accountability for decisions or errors related to AI remains poorly defined. Furthermore, excessive reliance on algorithmic results can undermine professional judgement. Data protection is also a major challenge, including patient confidentiality, informed consent and the possible misuse of data for commercial purposes. In addition, there are questions related to algorithmic performance, including the generation of false positives and biases resulting from unrepresentative training data sets that must be considered. Discrepancies with clinical*

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expertise can also pose a dilemma, forcing professionals to choose between their own judgement and the prediction made by AI.[3,4]

Among the various AI applications in MI, the use of AI-based denoising algorithms in Positron Emission Tomography/Computed Tomography (PET/CT) examinations stands out for its potential to reduce image acquisition time and radiation exposure, thus benefiting both patients and workflows.[5–9] Despite these advantages, concerns persist regarding the risks of generating false pathologies or image artefacts that could lead to misguided patient care decisions, affecting the adequate patient pathway.[5,10,11] The introduction of AI-based denoising directly impacts the workflow of radiographers, who are responsible for examination acquisition quality, and physicians, who analyze the examinations for clinical decision-making. Complicating matters further is the recognized lack of AI literacy among these professionals, which is a significant barrier to the adoption of this technology and its clinical implementation.[12–16]

To address these challenges, transparency and explainability are key elements to provide guidance and control over AI-driven processes in the adoption of AI technologies. Consequently, radiographers and physicians can build trust and are able to objectively analyze, understand and consider the limitations of AI algorithms in different MI contexts.[17–21]

The effort to off load the potential of AI's automation bias and to promote clarity over the reasoning behind its outputs have led to the development of the eXplainable Artificial Intelligence (XAI) field.[20–24] XAI can be defined as a set of features and techniques that create interpretable explanations for the process and predictions generated by an AI algorithm, with the goal to provide trust and understanding to their users.[20,25]

The field of XAI should extend beyond probabilities and computational complexities, avoiding the simplistic approach of using one AI system to explain another.[26] In addition to addressing the well-known “black box” problem inherent in AI implementation,[18,19] XAI must also consider the potential harm it may cause to patients. Therefore, interdisciplinary contributions, particularly from the social sciences, are essential to construct explanations that are both meaningful and useful to the end users.[27,28]

The development of XAI tools is therefore critical to overcome barriers to the AI adoption process, as it is directly linked to addressing the diverse range of factors that can influence AI acceptability. In this context, AI acceptability is affected by user-related factors, such as trust, system understanding, AI literacy, and receptiveness to technology; and also by system-related factors, including value proposition, self-efficacy, burden and workflow integration.[1,12]

Given these considerations, the aim of this study is to determine the key characteristics of an XAI tool aligning the radiographers' needs to facilitate the clinical adoption of AI-based denoising algorithms for PET/CT.

Methods

Study design

Two focus group (FG) interviews were conducted to explore the participants' attitudes, emotions, opinions, and needs regarding AI and XAI topics.[29] This method creates an interactive and dynamic setting, promoting richer discussions and deeper insights through group interactions.[30] Given that AI and XAI are rapidly evolving technologies, often perceived as complex or unfamiliar, the FG methodology was chosen as it effectively facilitates conversations around challenging subjects that might be difficult to adequately capture through one-on-one interviews.

Participants

Participants were enlisted by reaching out to the heads of nuclear medicine (NM) departments, encompassing various types (private, public, regional, and university) across Western Switzerland. A convenience sample of radiographers was attained by selecting volunteers based on a range of characteristics, including sex, institutional affiliation, years of experience, age, and modalities of practice.

Data collection

The initial FG comprised 6 participants (#1 to #6) and was conducted in a face-to-face format. The subsequent FG, involving 4 participants (#7 to #10), took place via the MS Teams platform (Microsoft, United States) according to the participants' preferences. The 50-min sessions were scheduled in the evening outside of normal working hours to accommodate more radiographers. Data collection stopped at saturation point, according to the moderator. Recordings were transcribed and edited to ensure accuracy.

The interviews were structured according to an interview guide.

- Presentation of the XAI definition allowing participants to be familiar with the concept.
- Presentation of two scenarios with images, one describing a patient with breast cancer that performed a follow-up F-18 FDG PET/CT scan. Images acquired with half the time (45 s) were reconstructed by AI, *matching* the ground truth (GT) (90 s), showing hepatic and vertebral metastases (Fig. 1a and b).
- The second scenario involving the same patient referred to a PET/CT to determine the cancer's stage, the AI-reconstructed images *did not match* the GT due to either the missing uptake of a lymph node or the appearance of an indeterminate liver lesion visible only on the AI images (Fig. 1c and d).

Based on these two scenarios, participants were requested to explore what they would like to ask to enhance their understanding on AI performance. Discrepancies in responses between these two scenarios were identified. The application of scenarios facilitated the users' transition to real-life contexts, drawing an empirical approach based on their experiences.[27,33–35]

- Discussion of the characteristics that should be incorporated into this XAI tool:
  - o Output format of the XAI tool, compared to existing formats described in the literature (*visual*, *textual*, *numerical*, *example-based*, *rule-based*)[21,22,36,37] (Fig. 2).
  - o Global versus local explanations: preferences for explanations of deep learning model functions at a general or individual (patient) level.
  - o Desired characteristics for the XAI tool
  - o Contribution/Utility of a XAI tool

Data extraction and analysis

The study examined the characteristics of the participants' ideal XAI tool using content analysis, following Wanlin's (2007)[41] three-step method.

- Pre-analysis: Selecting documents, forming hypotheses, identifying indicators, preparing for systematic organization.

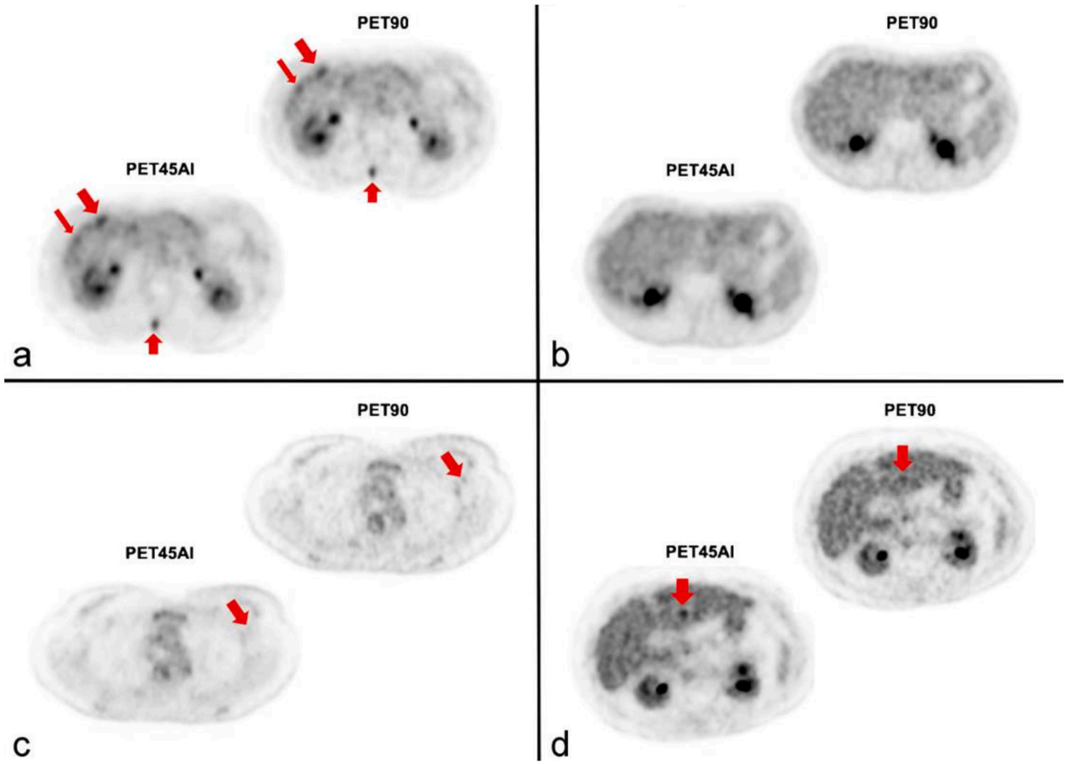

Figure 1. a-b: scenario 1: AI reconstructed PET/CT images (PET45AI) matching the GT (PET90) with a positive matching (**a**) and negative matching (**b**). **c-d: scenario 2:** AI reconstructed PET/CT images (PET45AI) mismatching the GT (PET90) by removing (**c**) or adding (**d**) a radiotracer uptake (taken from reference. The GT images were obtained following EANM recommendations[31] using a VEREOS digital PET/CT system (Philips Healthcare). Patients fasted for 6 h prior to receiving an intravenous injection of 3 MBq/kg of 18F-FDG. Image acquisition started 1 h after tracer administration in list mode. Each subject underwent two PET scans: the first with 90 s per bed position, and the second with a reduced duration of 45 s. The 45-s acquisitions were subsequently processed with SubtlePET™ (Subtle Medical, Stanford, USA; distributed by Incepto, France), a post-reconstruction denoising tool for PET images that is FDA-cleared and CE-marked for 18FFDG PET.[32] Further details regarding the acquisition protocol or image quality can be found in the study by Wetyz et al.[9] This article is licensed under Creative Common Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format. Link: https://creativecommons.org/licenses/by/4.0/).

- Material exploitation: Categorizing and counting data while preserving original meaning.
- Processing, interpretation, inference: Exploring themes, establishing connections, employing statistical methods as needed.

The analysis was reviewed and discussed with another team member to ensure clarity/precision.

Ethics

To maintain ethical standards and ensure confidentiality, participants were informed about the study and signed an agreement. Recordings were destroyed and data were deidentified during transcription.

Results

Participants

Ten volunteer radiographers, evenly distributed by sex, participated in the study, with a mean age of 38.4years (31–60years). They represent diverse practice settings: university (n = 3), regional hospitals (n = 3) and private clinics (n = 4). All participants were proficient in NM. Additionally, five of them demonstrated expertise in supplementary imaging modalities (Table 1).

Main areas of explainability needs

After being briefed on the XAI concept, participants were able to formulate their needs to ensure the algorithm's accessibility and comprehensibility designed to enhance PET/CT image quality according to each scenario.

As the scenario evolved, radiographers presented several changes and clarifications. Their requirements for the first scenario were related to training, technical information as data used and limitations, the context of use, scientific articles and a confidence score. Only one participant required having nothing due to high workload and time constraints.

> "*As a radiographer, using a machine with a super-high patient flow because we're working more and more, I wouldn't need anything ….we trust the algorithm …" (Participant#7).*

After analyzing the second scenario on image hallucination in staging and its impact on treatment, radiographers refined their needs. All participants recommended a confidence score. Essential information such as false-positive/false-negative rates, physician-AI performance comparisons, and threshold tests for potential reductions in activity and acquisition time were presented as necessary. The critical eye of a professional and quality control were identified as requirements.

> *"The use of AI should not discourage us from observing and evaluating our images. A professional's critical eye must be kept on the results." (Participant#10).*

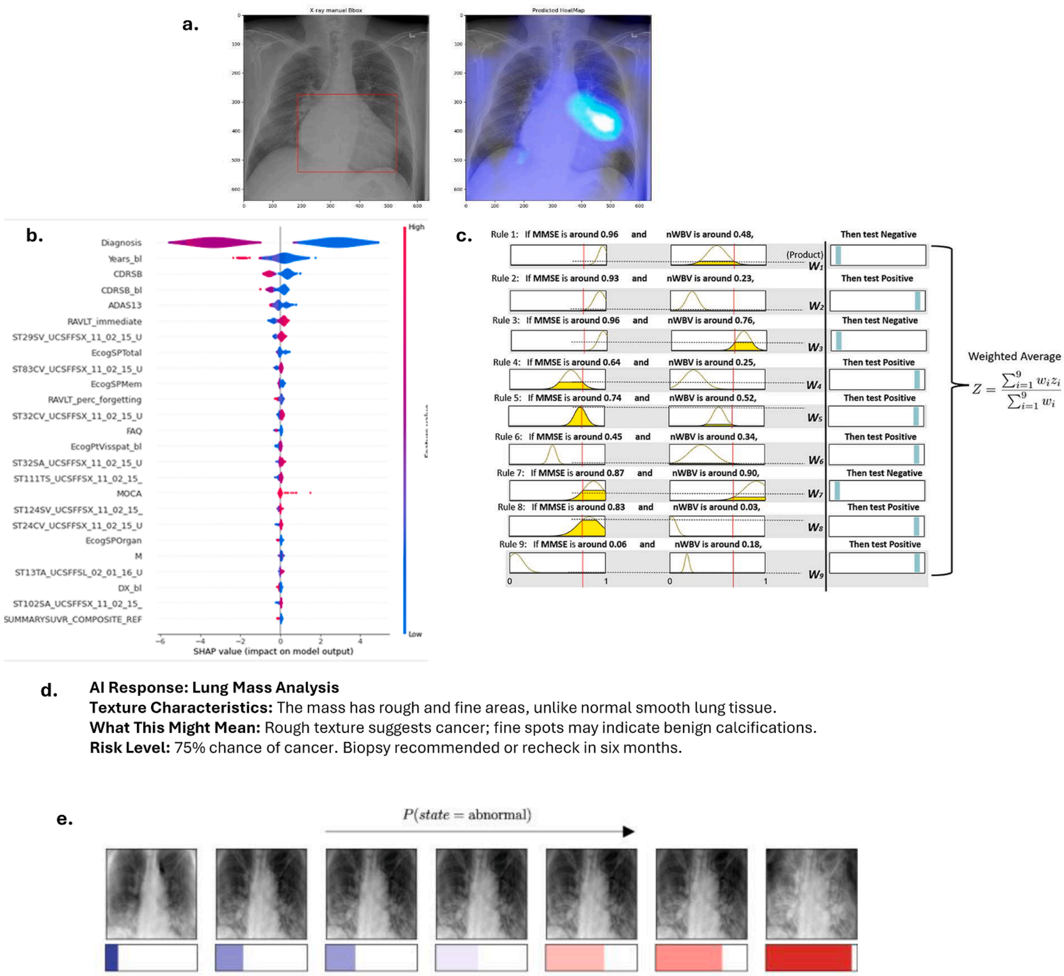

Figure 2. Different output formats presented to participants: a. Visual: Heatmap visualization for cardiomegaly; **b. Numerical:** The violin plots show the SHAP value[38] (This is an open access article distributed under the terms of the http://creativecommons.org/licenses/by/4.0/. Cliquez ou appuyez si vous faites confiance à ce lien.">Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium).; **c. Rule-based:** An illustration in the context of making the rules used for 2 characteristics in a clinical decision-support diagnosis of dementia transparent[39] (This is an open-access article distributed under the terms of the http://creativecommons.org/licenses/by/4.0/. Cliquez ou appuyez si vous faites confiance à ce lien.">Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted); **d. Textual**: Example of textual explanations; **e. Example-based**: TraCE generates counterfactual explanations based on diagnoses by incrementally incorporating pertinent patterns into various query images belonging to healthy individuals, thereby enhancing the probability of their classification into the abnormal category[40] This article is licensed under Creative Common Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format. Link: https://creativecommons.org/licenses/by/4.0/).

Table 1
Participants' profile and AI/XAI knowledge and training description.

N°	Sex	Age	Experience (Years)	Knowledge AI	AI education	Knowledge XAI	Hospital Type	Modalities
#1	F	50	23	Basic	–	–	Regional	NM, CT, MRI, Rx
#2	M	33	7	Basic	–	–	Regional	NM, CT, Rx
#3	M	31	5	Basic	CPD	–	University	NM
#4	M	60	38	Basic	–	–	Private	NM
#5	F	36	8	–	–	–	Private	NM, CT, Rx
#6	F	37	3	–	–	–	Private	NM, Rx
#7	M	32	6	–	–	–	Regional	NM
#8	F	35	1	–	–	–	University	NM
#9	F	33	4	–	–	–	University	NM
#10	M	37	12	–	–	–	Private	NM, Rx

F:Female; M:Male; CPD:Continuing Personal Development NM:Nuclear Medicine; CT:Computed Tomography; MRI:Magnetic Resonance Imaging; Rx:Radiography; Radiographers:#1–6: on site FG(1) & #7–10 online FG(2).

Two participants also compared the limits of AI performance with the current limitations of PET technology, the healthcare system, or NM physicians' diagnostic errors.

"We also know very well that the tracers we use have problems linked to spatial resolution, … then it is a question of knowing what tolerance you are ultimately putting on your algorithm? … Well, you must tolerate a kind of margin of error." (Participant#7).

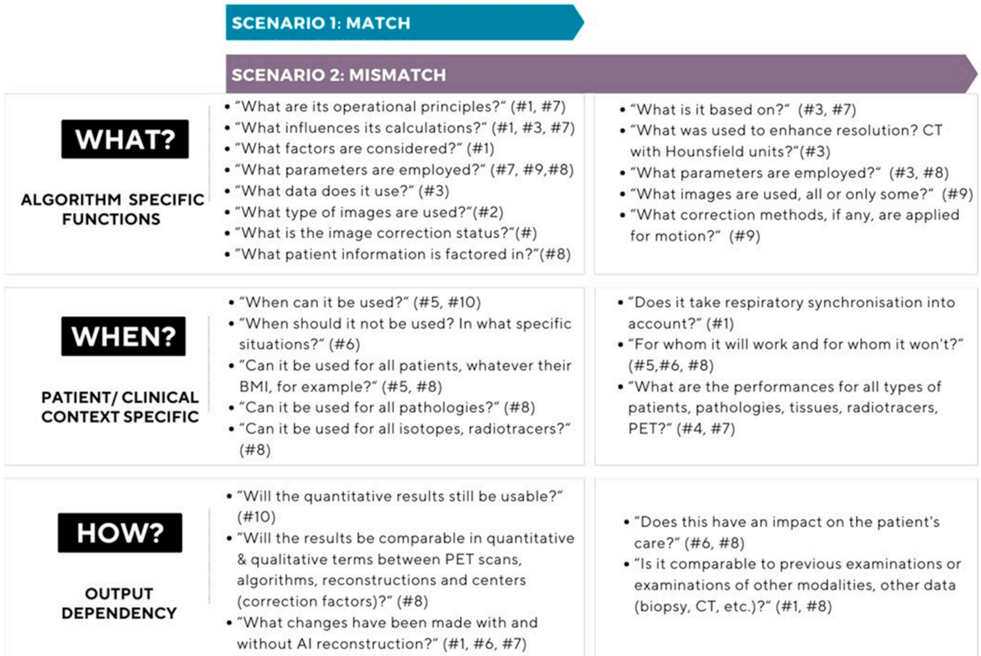

Figure 3. The main questions of radiographers to understand AI outcomes via the XAI Tool.

"Does not this amount to the same problem as someone who lives in a town that does not have a PET scan nearby? Well, they are also less likely to have their cancer detected because they do not have this technology at their fingertips as much." (Participant#5).

The following requirement was related to formulate questions that users might ask about AI, with each explanation treated as an answer to these questions. The inquiries that users would like to ask after seeing the results of the scenarios were grouped in 3 categories: algorithm specific functions, patient/clinical context, and output dependency. The questions relating to the algorithm functions that participants would like to ask were mainly '*what*' questions concerning the technique, data and parameters. Those concerning the patient/clinical context were '*when*' questions to find out situations in which the algorithm could be used, for example, patients' types, pathologies, radiotracers and tissues. Finally, the questions concerning the output dependency were linked to its consistency from both a qualitative and a quantitative point of view and its integration into the patient's care pathway. The questions did not show any real difference depending on whether they corresponded to the GT (Fig. 3).

XAI characteristics

Global or local explanations

Radiographers were required to present their preferences: global or local explanations. Two of them "*would be interested in a general explanation because we do not have time to look at each patient individually"* (*Participant*#9). While three participants would prefer local explanations for multiple reasons, such as tracking, personalized explanations, quality criteria or requirements. *"Every patient is different, and every situation is different. Every pathology is a little different. And I think that is good if it is a bit personalized. for a question of tracking too ….Just as we have a dose report, we need an XAI report." (Participant#5).* Three others would like both types of explanation, and the local explanation to appear only if they have any doubts. Two participants did not answer on this subject.

In the second scenario, four participants changed their views: two switched to local explanations, while the other two preferred having both global and local explanations.

Output or explanation formats

The frequency of *visua*l, *numerical*, and *example-based* formats was highlighted five times. Participants also introduced an unconventional format, *oral*, as a conversational agent, also mentioned five times because of its adaptability to the user level and needs. Participants preferred numerical ($n = 5$), oral ($n = 4$) and visual/example-based ($n = 3$) formats. Five participants indicated a preference for *mixed* formats (Fig. 4).

The visual format was much discussed and was often associated with the example-based format. The example of heatmaps was interesting for two participants, but always accompanied by numerical because *"The visual, …., I do not know what color it is, I am going to say yeah, it is pink, and in fact you are going to say oh no, it is a bit redder. Whereas if a number is there, there is no way of being subjective."(Participant#2).* The numerical was described as a confidence score for five participants. Example-based triggered a lot of ideas for comparisons such as between AI reconstructions and raw data, previous patient examinations or imaging from other modalities.

Attributes XAI tool

The desired characteristics for XAI tools were identified and classified into two themes: appearance and usability (Fig. 5). The tool should feature visually appealing iconography, interactivity, and adaptability to the user's level and specific needs.

Contribution/utility

Several benefits of this XAI tool were identified, including increased confidence in the algorithm mentioned by 9 participants. This was equally followed by improved understanding and

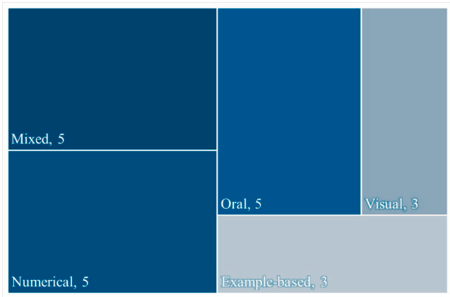

Figure 4. Frequency of preferences regarding XAI tool output formats presented by radiographers.
Based on the output formats presented to participants (Fig. 3). **Mixed**: with a minimum of two different formats; **Oral:** Not yet used in XAI taxonomy.

workflow impact (n = 4). Additional benefits included enhancing the users' technical expertise, supporting decision-making, ensuring quality assurance, facilitating AI implementation, increasing interest in the technology, and contributing to sustainability, each reported twice.

Discussion

This qualitative study aimed to determine the characteristics of an XAI tool that aligns with the radiographers' needs, thereby promoting their confidence in adopting an AI-based denoising algorithm for PET/CT clinical applications. The findings reveal two distinct levels of explanation needs among radiographers: a basic level suitable for routine clinical contexts and a more detailed level for complex and unusual scenarios.

At the first level, radiographers emphasized the need for simplicity and efficiency in XAI tools to build confidence and understand AI algorithm results without disrupting workflows. They favored global explanations addressing "what" questions, focusing on the algorithm's functions without case-specific details. A numerical confidence score was particularly valued for offering a quick and objective measure of the algorithm's reliability, meeting the need for concise information. These preferences suggest a “basic” level of explainability that optimally integrate into routine practice, ensuring efficiency and focus on patient care. This finding aligns with existing literature on AI integration in healthcare, which highlights the importance of designing simple and efficient AI tools[42–45] that seamlessly fit into clinical workflows to avoid increasing cognitive load or causing workflow disruptions.[12,42,44]

In contrast, the second level of explanation needs arises in complex clinical scenarios where AI outputs could significantly impact patient outcomes. Radiographers expressed a need for deeper understanding and trust in the AI tool to support their decision-making in cases such as staging indications, rare pathologies, unique patient characteristics, or low confidence scores. These explanations should be adaptable and combine multiple formats including numerical data, visualizations, textual descriptions, or example-based outputs. For instance, visual heatmaps highlighting image areas influencing AI decisions, or text summaries explaining the reasoning behind the algorithm's output can provide valuable insights. While oral explanations may pose ethical or practical challenges, interactive conversational agents in text form could offer a user-friendly alternative.

The shift towards local and personalized explanations in complex scenarios reflects the radiographers' responsibility for patient safety and the need to critically evaluate AI tools. By offering deeper insights into the AI reasoning, the XAI tool can help radiographers build trust in the technology and ensure that it supports high-quality patient care. Ethical considerations are critical and in accordance to medical ethical principle of ‘do no harm’, it is essential that XAI tools minimize the potential harm that AI use can cause to patients if misinterpreted or misapplied.[3] Therefore, interdisciplinary contributions, including from the social sciences, are needed to develop high-quality and useful explanations that improve patient care without introducing new risks.[24,26,46]

To address the radiographers' diverse needs across clinical settings, XAI tools should offer adaptable, user-centered features.[26,27,47] A tiered approach to explanations can manage cognitive load by providing essential information, such as a numerical confidence score, by default, while allowing radiographers to access more detailed visual or textual explanations through interactive elements as needed. This layered design helps radiographers obtain sufficient detail without overwhelming them with excessive information, thus supporting effective decision-making.[48–50]

Contextual adaptability is also essential. The XAI tool should create explanations based on patient-specific factors, such as pathology and imaging characteristics, enhancing relevance and usefulness. By providing explanations directly applicable to individual cases, the tool supports radiographers in making informed decisions aligned with the specific needs of their patients.[51–53]

Designing intuitive interfaces that facilitate easy navigation between different levels of information can further enhance usability. A user-friendly interface ensures that professionals can efficiently access and interpret the information they need, whether they require a quick overview or a comprehensive explanation. Incorporating multiple output formats – numerical, visual, and textual – allows users to choose the most appropriate method for the situation, accommodating personal preferences and varying levels of expertise.[27,54,55]

Training and education are essential to promote the effective use of XAI tools. Targeted training provides radiographers and healthcare professionals with the essential skills to correctly interpret AI results. Continuing professional development helps maintain their competence and confidence by informing them of advances in AI and best practice.[13,14,56,57] Comprehensive education about AI, including its benefits, limitations, biases and ethical

Figure 5. Attributes mentioned by radiographers that XAI tool should have. In **a** characteristics related to **appearance**; in **b** characteristics related to **usability**. The size of the words depends on the frequency with which they are cited. The larger the word, the more often it is cited by radiographers.

considerations, ensures informed decision-making, reduces risks and improves patient care.[58,59]

This study has several limitations. First, the small sample of ten radiographers in two focus groups limits the generalizability of findings, despite consistent observations such as output format preferences, adaptive explanations, and tool usefulness. Second, the participants' limited familiarity with AI and XAI made it difficult to fully articulate their explainability needs and preferences. Third, the exclusive focus on a single AI task (PET/CT denoising) raises uncertainty about the transferability of results to other medical imaging or healthcare applications.

Future research should include a larger and more diverse MI population to validate and extend the findings from this study. It should also explore radiographers' needs and preferences across a variety of AI applications and settings, as well as implementing XAI tools in the real-world to evaluate its effectiveness, usability and influence on technical and clinical decision-making and patient care.

Conclusion

This study highlights the importance of offering explanations at two levels when integrating AI-based denoising algorithms into clinical PET/CT practice for routine clinical tasks, radiographers prefer simple global explanations, such as numerical confidence scores, to ensure efficiency without disrupting workflows. When deeper understanding is necessary, a detailed explanation layer is delivered through mixed formats (numerical, visual, textual) enhancing trust and supporting informed decision-making.

Implementing a tiered approach to explanations, ensuring contextual adaptability, and providing adequate training and education are key strategies for the adoption of XAI tools. Ultimately, by enhancing the radiographers' ability to understand and validate AI reasoning, XAI tools can contribute to quality assurance and support informed decision-making processes, improving patient care and health outcomes.

Ethics approval

The research project underwent review by the Vaud Cantonal Commission on Ethics (Request #2023-01539), which determined that the project falls outside the scope of the Law on Research on Human Beings (LRH) and does not require further ethics commission authorization. FG did not involve health-related topics, or the collection of personal health data as defined by Article 2 of the LRH.

Informed consent was obtained from all participants involved in this study.

Availability of data and material

The data used during the current study are available from the corresponding author upon reasonable request.

Authors contribution

Mélanie Champendal: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Writing-original draft, Writing-review and editing. **Ricardo Teresa Ribeiro**: Formal analysis, Writing-original draft, Writing-review and editing, Supervision. **Henning Müller**: Conceptualization, Methodology, Writing-review and editing, Supervision. **John Olivier Prior**: Conceptualization, Methodology, Writing-review and editing, Supervision. **Cláudia Sá dos Reis**: Conceptualization, Methodology, Investigation, Writing-review and editing, Supervision.

Declaration of Generative AI and AI-assisted technologies in the writing process

Nothing to disclose.

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Conflict of interest statement

None.

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