



Nuclear medicine technologists practice impacted by AI denoising applications in PET/CT images

M. Champendal^{1,2,*}, R.S.T. Ribeiro¹, H. Müller^{3,4}, J.O. Prior^{2,5}, C. Sá dos Reis¹

¹ School of Health Sciences HESAV, HES-SO, University of Applied Sciences Western Switzerland: Lausanne, CH, Switzerland

² Faculty of Biology and Medicine, University of Lausanne, Lausanne, CH, Switzerland

³ Informatics Institute, University of Applied Sciences Western Switzerland (HES-SO Valais) Sierre, CH, Switzerland

⁴ Medical Faculty, University of Geneva, CH, Switzerland

⁵ Nuclear Medicine and Molecular Imaging Department, Lausanne University Hospital (CHUV): Lausanne, CH, Switzerland

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ABSTRACT

Purpose: Artificial intelligence (AI) in positron emission tomography/computed tomography (PET/CT) can be used to improve image quality when it is useful to reduce the injected activity or the acquisition time. Particular attention must be paid to ensure that users adopt this technological innovation when outcomes can be improved by its use. The aim of this study was to identify the aspects that need to be analysed and discussed to implement an AI denoising PET/CT algorithm in clinical practice, based on the representations of Nuclear Medicine Technologists (NMT) from Western-Switzerland, highlighting the barriers and facilitators associated.

Methods: Two focus groups were organised in June and September 2023, involving ten voluntary participants recruited from all types of medical imaging departments, forming a diverse sample of NMT. The interview guide followed the first stage of the revised model of Ottawa of Research Use. A content analysis was performed following the three-stage approach described by Wanlin. Ethics cleared the study.

Results: Clinical practice, workload, knowledge and resources were the 4 themes identified as necessary to be thought before implementing an AI denoising PET/CT algorithm by ten NMT participants (aged 31–60), not familiar with this AI tool. The main barriers to implement this algorithm included workflow challenges, resistance from professionals and lack of education; while the main facilitators were explanations and the availability of support to ask questions such as a “local champion”.

Conclusion: To implement a denoising algorithm in PET/CT, several aspects of clinical practice need to be thought to reduce the barriers to its implementation such as the procedures, the workload and the available resources. Participants emphasised also the importance of clear explanations, education, and support for successful implementation.

Implications for practice: To facilitate the implementation of AI tools in clinical practice, it is important to identify the barriers and propose strategies that can mitigate it.

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Introduction

Positron emission tomography/computed tomography (PET/CT) is a hybrid medical imaging (MI) modality clinically used for physiological studies mainly in neurology, cardiology and oncology.¹ Deriving from nuclear medicine (NM), PET examinations

* Corresponding author. Avenue de Beaumont 21, 1011 Lausanne 076/221.97.70, Switzerland.

E-mail addresses: melanie.champendal@hesav.ch, melanie.champendal@unil.ch (M. Champendal), ricardo.ribeiro@hesav.ch (R.S.T. Ribeiro), hennig.mueller@hevs.ch (H. Müller), john.prior@unil.ch (J.O. Prior), claudia.sadosreis@hesav.ch (C. Sá dos Reis).

provide physiological information of organs using radiopharmaceutical products (radiotracers) while CT provides the morphological details of the anatomical region under study. This hybrid imaging delivers radiations to the patient from the CT scan and from the injected radiotracer. The 2-deoxy-2-[fluorine-18] fluorodeoxyglucose (¹⁸F-FDG) is the most commonly used tracer for oncological indications to evaluate the staging, therapy response and follow-up.² Patients often undertake multiple scans, leading to cumulative radiation exposure. This accumulation can present risks, particularly for children, including stochastic effects such as the potential development of radiation-induced cancer.^{3–5}

While CT imaging typically has a relatively short acquisition time, PET requires longer time, being more challenging for certain

patients like claustrophobic, paediatric or patients under pain. Image acquisition depends also on the injected activity and PET types. Reducing the injected activity may be necessary in situations where there is a shortage of radiopharmaceuticals or in regions where resources are limited. A reduction in the quantity of product has a direct impact on the overall procedure's costs. It is therefore an interesting strategy for improving the cost-effectiveness of FDG-PET examinations.⁶ However, reducing both effective dose and acquisition time can compromise image quality (IQ), resulting in a lower Signal-to-Noise-Ratio⁷ impact the examination outcomes.

Iterative reconstruction algorithms, image filtering, post-processing,⁷ and digital PET/CT^{8,9} have been developed to address the trade-off between effective dose and IQ. With these solutions several challenges and requirements arrived such as important computational resources, reconstruction time (iterative techniques), the introduction of blurring, artifacts or over-smooth images (Image filtering, post-processing),⁷ or even the need for a new equipment (Digital PET systems).^{8,9}

A new paradigm has surfaced with the advancement of Artificial Intelligence (AI)-based denoising algorithms,^{7,10–17} due to the capacity of overcoming the main limitations of the previous techniques, but it encounters criticism and concerns for different reasons: (i) health professionals' lack of AI literacy, (ii) fear of the “black box” effect with potential to generate false pathologies and influencing patient outcome.^{7,18,19} Among them, nuclear medicine technologists (NMT) have expressed deep concerns about their lack of knowledge in the fundamental principles of AI, as well as a lack of proficiency and confidence in using this technology in clinical practice.^{20–23} Additionally, there are apprehensions regarding the implementation of AI technology due to its potential to generate artifacts.^{7,19} The literature reports the possibility of the apparition or extinction of hyperactivity which does not correspond to the ground truth.^{7,19,24}

Despite the resolution of current technical limitations, including limited availability of high-quality annotated data, crucial for effective AI models training,^{25–27} it becomes essential to develop a careful AI implementation strategy to effectively overcome the steep adoption learning curve. This means ensuring technical feasibility, but also aligning the implementation process to the users' needs and capabilities. The successful adoption of a new technology depends largely on the willingness and ability of users to integrate it into their workflows and practices. In addition, it is essential to recognise that the adoption of AI technology in healthcare settings is a multifaceted process influenced by various factors, including the clinical practice environment and its diverse dimensions such as service organisation and workflow dynamics; the potential adopters' perceptions, and scientific evidence.^{28–30} Among the different implementation of innovation frameworks, the revised Ottawa Model of Research Use (OMRU),²⁸ derived from the theory of change, presents a planned action model. OMRU involves studying how users perceive the AI value and usefulness in their daily practice.^{31,32} In PET/CT image denoising task, with the purpose of reducing patient dose and/or acquisition time, the primary users are the NMT in collaboration with the NM physicians. The NMT play a crucial role in ensuring that IQ standards are attained, and they are responsible for the technical validation of the outputs generated by algorithms.³³ Understanding reconstruction methods, knowing the technical parameters influencing image quality, taking responsibility for ensuring that images are optimal for diagnostic purposes and having a critical eye are all part of the knowledge and skills required to start clinical practice as NMT according to the European Association of Nuclear Medicine.³⁴ To our knowledge, no study contextualised to the specific task of image denoising has been carried out, including NMT.

The aim of this study was to identify aspects that need to be analysed and discussed to implement an AI denoising PET/CT algorithm in clinical practice, based on the representations of NMT from Western-Switzerland, highlighting the barriers and facilitators associated to.

Methodology

Study design

Two focus group (FG) interviews were conducted, enabling data collection from a small group, fostering discussions on the topic of interest. This approach stimulates group dynamics, facilitating interactions among participants.³⁵ FGs allow researchers to gather data on attitudes, feelings, opinions, needs, and participants' motivations, encouraging follow-up questions and reflections for comprehensive and in-depth data.³⁶ Given the complexity of discussing AI, that many NMT feel unfamiliar with, FG are advantageous over one-to-one interviews, commonly used to explore challenging topics.³⁵

Participants

Participants were recruited by contacting all NMTs' heads of all types of MI departments (private, public, regional and university) in the Western-Switzerland. A diverse sample of NMTs based on the volunteers that applied to participate was achieved mixing different characteristics such as sex, type of institution, years of experience, age, and imaging modalities in which they were practicing.

Data collection

The first FG involved 6 participants (#1 to #6) in a face-to-face setting, while the second, involving 4 participants (#7 to #10), was conducted via the MS Teams platform (Microsoft, United States) between June and September 2023 according to participants' preferences. Sessions, lasting approximately 40 min each, were held in the evening to facilitate the NMTs' availability. The moderator, expert in AI, decided to stop data collection when saturation was reached. A co-facilitator, FG methodology expert, attended the first session for clarification in the conduction of such method. Recordings were made using two digital recorders and transcribed using Google Docs, then reviewed and edited by a researcher for accuracy.

The interviews were conducted following a structured interview guide (Table 1), which aligns with the OMRU.²⁸ The questions covered aspects concerning potential adopters, like their familiarity with the innovation, reactions to change, competencies, past experiences, and any concerns or inclinations towards adoption.²⁸ The guide was divided into two different sections:

Table 1
Examples of probing questions.

How familiar are you with this type of algorithm?
Is it applied in your departments? How is it used?
What do you think of this AI tool?
How do you position yourself in relation to this algorithm?
As future users, what do you think would make it easier to implement this AI tool?
What would be the obstacles to the implementation of this AI tool?

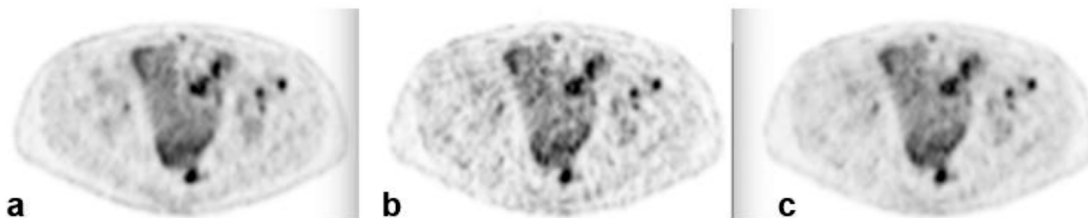


Figure 1. PET/CT images a: acquired in 2 min/bed position (Groundtruth), b: 30 s/bed position and c: corresponding 30sec AI-enhanced results.³⁷

- a) Introduction to the PET/CT denoising algorithm to collect its impact on their clinical practice. After an explanation and an example of images before and after AI enhancement were given to start the discussion (Fig. 1).
- b) Monitoring the barriers and facilitators of implementing denoising algorithm in their clinical practice.

Data extraction and analysis

A content analysis was carried out, using the three-stage approach described by Wanlin (2007)³⁸:

- Pre-analysis phase involving the election of relevant documents, initial reading, formulating hypotheses and objectives, identifying indicators, and preparing the material. This step assists the researcher in effectively harnessing the data for a systematic analysis.
- Material exploitation phase aiming to organise data using specific categories/codes and counting methods while preserving the original meaning.
- Processing, interpretation, and inference phase in content analysis to explore themes in greater depth using the literature, establishing links between them, discovering differences and contradictions, and using statistics when appropriate.

Codes and themes were reviewed and discussed with another member of the team to make them understandable and more precise.

Ethics

To ensure ethical standards, participants were fully informed about the study and provided consent. Recordings were erased, and data deidentified during transcription. The research was approved by the Vaud Cantonal Commission on Ethics in Human Research (Req-2023-01539), which determined it fell outside the scope of the Law on Research on Human Beings (LRH) and did not require further ethical clearance. Group interviews do not concern disease or the structure and function of the human body within the

Table 2 Participant profiles and their AI knowledge and training.

ID	Sex	Age	Years of experience	knowledge of AI principles	AI education	Hospital type	Modalities
#1	Female	50	23	Basic	–	Regional	NM, CT, MRI, Rx
#2	Male	33	7	Basic	–	Regional	NM, CT, Rx
#3	Male	31	5	Basic	CPD	University	NM
#4	Male	60	38	Basic	–	Private	NM
#5	Female	36	8	None	–	Private	NM, CT, Rx
#6	Female	37	3	None	–	Private	NM, Rx
#7	Male	32	6	None	–	Regional	NM
#8	Female	35	1	None	–	University	NM
#9	Female	33	4	None	–	University	NM
#10	Male	37	12	None	–	Private	NM, Rx

Note: NM: Nuclear Medicine; CT: Computed Tomography; MRI: Magnetic Resonance Imaging; Rx: Conventional Radiography. NMT #1–6: on site FG (1) & NMT#7–10 online FG (2).

meaning of art. 2 of the LRH, and do not involve the collection of personal data relating to health.

Results

Participants

Ten volunteer NMTs (5 women; 5 men) with a mean age of 38 (range 31–60 years) participated in this study. Their place of practice maps the different types of institutions namely university hospitals (n = 3) and private clinics (n = 4). Although, they were all experts in NM, five of them also worked in other imaging modalities (Table 2).

NMT representations on the adoption of AI technology for the denoising task in PET/CT clinical practice

Although the participants were familiar with the same type of denoising algorithm in CT and MRI, none was aware of AI-based denoising algorithms for PET/CT. The panel discussion gave rise to four themes: clinical practice, workload, knowledge and resources (Fig. 2).



Figure 2. Themes and codes identified by focus group participants about the impact of PET/CT AI image denoising tool.

Clinical practice

The implementation of AI technology was perceived by the participants as offering numerous benefits to the clinical practice, enhancing efficiency in PET/CT examination workflow by reducing the acquisition time and overall examination's costs.

“Either we increase the number of machines to be able to fit all these patients, or we optimise the protocols. And I think this is a very good way of limiting costs ... well thanks to AI-tools like that.” (NMT#5)

If its performance is proven, the incorporation of such algorithm is perceived as providing improved patient experience throughout the examination, since it “promises” a safer analysis (reducing radiation exposure) without compromising diagnostic quality (enhanced image quality). The workflow optimisation achieved by the improved acquisition's time also may lead to a reduction of patient's waiting time, increasing their comfort.

“If it can improve image quality, and therefore the possibility of diagnosis, while at the same time improving the patient's experience in nuclear medicine, whether that means less radiation or less time spent on the machine, I think that would be a good thing.” (NMT#7)

“For patients in pain, for example, it's true that if we can save time, well that's precious.” (NMT#6)

Workload

Participants identified several concerns regarding organising and managing a nuclear medicine department, including existing work processes, health care professionals' involvement and needs of resources' allocation. NMTs were concerned that reducing examination time may lead to an increase in the number of patients addressed per day, thus increasing workload. This would have implications for nuclear physicians, who would have more reports to write, impacting their interactions with NMTs and patients.

“NM Physicians have so many examinations to do that they are constantly being called by the referrals because they have not done their reports.” (NMT#3)

“It's also organisational. I mean, suddenly you're going to see 15 patients in a day instead of 8. Anyway, you have to reorganise everything. Both on the medical side and on the NMT side ... but you're not still enough.” (NMT#1)

Additionally, the previously mentioned workflow optimisation may lead to an increased workload, in an assembly-line approach, leaving limited time to communicate with the patient.

“I can find one slightly negative point, I say to myself that for us, as NMTs, ... it is like working on a factory production line, because we're going to be putting even more patients on the line every day.” (NMT#5)

“You do not really talk to the patient; you do not have enough time.” (NMT#3)

“Manufacturers ... told us with an angelic air, that as we were going to save time on patients, we would have more time to talk to the patient, assist them and so on. That is what they told the NMT. I can

imagine that they did not say the same thing to the hospital managers or to the nuclear physicians.” (NMT#4)

Therefore, it is important that managers consider how AI implementation affects the interaction between NMT, physicians and patients. Participants outlined that the overall scheduling optimisation should balance the increased examination volumes with the time for patient interactions and inter-professional communication.

In addition, department managers must consider if the installed IT infrastructure is not obsolete and possesses the computational capacity needed to support such implementation, encompassing aspects such as data storage, processing power, and network capabilities so that machines do not break down frequently.

“There is also the reality of what we do in clinical practice. Do our machines and computers have the capacity to adapt ... ? ... The machine breaks down 2 or 3 times a day, it is likely to be really problematic and I think that in the end, the benefit for the patient will not be very great.” (NMT#9)

Knowledge

Knowledge dimension emerged from the verbatims related to participant projections of the utility of this algorithm in clinical practice. Codes identified this process of appropriation and the future needs of users. This algorithm was compared with that used by the participants to reduce metal artifacts and the necessary comparison at the beginning between the image with and without corrections applied by the users, and then the routine after several years of experience to only look at the corrected images.

“In a few years, it will have become normal to use these image reconstruction algorithms, as it is simply a different type of image reconstruction.” (NMT#7)

There was a strong interest in delineating the roles of individuals at each stage of AI implementation, with particular emphasis on the inclusion and recognition of NMTs in the process.

“There would still have to be added value for the NMT too. That would mean getting involved in the implementation. The person who could be asked more detailed questions could be a sort of reference NMT with more advanced training to make the role evolved. Because if it's just a tool, as I was saying earlier, that allows you to go faster. Faster, dumber, I mean, you don't really need to be an NMT to press the button when it flashes, do you?” (NMT#4)

Participants questioned the existence of scientific evidence validating the effectiveness, performance, and safety of these types of algorithms.

“There are several studies, I suppose, about denoising? I imagine that these studies are following a scientific approach, no?” (NMT#4)

Furthermore, participants emphasised the significance of conducting “use case analysis” approach to comprehend how the algorithm could be effectively integrated into existing workflows. They provided scenarios where the algorithm could be applied, involving specific clinical contexts when the AI algorithm could improve the examination outcomes and patient experience/comfort.

“I can imagine the situation where it is already being proposed to people who cannot stand on the table ... someone with hyperalgesia and multi-metastatic disease.” (NMT#10)

Additionally, concerns regarding the resources and technical expertise required for this clinical implementation were raised. Thus, raising critical adoption challenges with respect to lack of awareness and understanding of AI. Participants suggested that lack of understanding or NMTs who will not be interested in AI may not embrace this new technology.

“If you don't understand anything, if you don't want to understand ... then you won't know, you'll be lost and you'll be up against the wall. But you still have to join. Because those who don't are going to be obstacles, and that's going to be complicated.” (NMT#1)

Resources

Sustainable usage of resources was also discussed by the participants. Implementing this algorithm can have a positive impact on resources as it can enable a reduction of radiotracer production. Indeed, the ability to inject a smaller amount of radiopharmaceutical allows for smaller production of the latter and helps mitigate shortages.

“There are problems in obtaining products, so there will be fewer of radiopharmaceuticals available ... I think that afterwards it is very important to use less product.” (NMT#1)

“Thinking that we can reduce activity ..., because ..., we really have a shortage. We have had to cancel patients ..., but with a tool like this, maybe we would not need to cancel so many patients.” (NMT#3)

NMTs also highlighted the negative impact on energy consumption due to an increased number of examinations and equipment overuse, leading to rapid facility deterioration and increased maintenance. Additionally, there were concerns about the strained IT infrastructure, often resulting in frequent breakdowns. There is a fear that the implementation of AI-based algorithms may further exacerbate these issues because the current system is at the limit of what it can handle.

“Often we have already problems getting everything done, all the recons we have to do daily ... We already have quite a few problems because sometimes PET can't keep up at all and I wonder if algorithms like that aren't going to take up a lot of space and electricity. If we now have frequent database breakdowns on PET/CT, for

example, I don't know if that's going to cause any more problems.” (NMT#9)

These concerns about frequent breakdowns also generated another discussion about the impact of MI departments on the environment due to increased electricity usage.

“ In terms of sustainable development, ...there are even other problems related to the MI usage as the impact on the environment, because each time you restart or each time you have to carry out checks, ..., that also uses the machine, it is not on standby, asleep, and then you turn it on again ..., so I am not sure that our machines can also keep up.” (NMT#8)

Human resources were also underlined as a critical point, with exhaustion and consequent decline in the well-being of the healthcare professionals involved in MN departments. Concerns arise regarding the potential increase in the numbers of examinations, highlighting the challenge of managing them effectively due to the shortage of personnel.

“Both on the medical side and the NMT side ... we are not enough anyway.” (NMT#1)

Facilitators and barriers

The facilitators and barriers identified by the participants on the implementation of AI technology, for denoising tasks, in PET/CT clinical practice are summarised in Table 3.

The main facilitators identified were the availability of explanations accompanying the algorithm usage with a “local champion” available to support the use of such tool and to respond to subsequent questions.

“Explanations, information ... adapted to the level ... personalised ... to each person in the best of worlds.” (NMT#1)

“The explanation is extremely important for learning to trust the algorithm.” (NMT#7)

“If we can contact someone who might have an idea, ...an NMT but, for example, someone who has done the programming or a computer scientist.” (NMT#3)

Participants also identified as facilitators the education of healthcare professionals, involvement in the implementation process, a gradual transition with comparisons, use-case examples specific to the equipment and patients, interoperability between different equipment and manufacturers, a collaborative

Table 3
Barriers and facilitators identified by participants for AI implementation in MI departments.

Facilitators	Barriers
<ul style="list-style-type: none"> • Explanations • Availability of support available/“local champion” • Education and training • Implementation phase comparisons/use cases • “Quality label” attributed to the department: skills, education, new technologies. • New generation of healthcare professionals • Involvement in implementation • On-site demonstration: added value (on-site cases with on-site devices). • Examples of where it works and where it does not. • Interoperability • Transparency (patients, reports, etc.) • Partnership (NMT, physicians, patients, and clinicians) 	<ul style="list-style-type: none"> • Workload increase • Resistance from professionals • Lack of education • Loss of skills • Misunderstanding • Work organisation • Lack of recognition (role, expertise) • Hierarchy • New and unusual image quality

partnership between NM professionals, patients and clinicians, new generations of more technophile professionals, the presence of a quality label and publicity (use of cutting-edge technology) and financial benefits for the services.

“Being highly invested in the implementation process “(NMT#2)

“Compare the normal acquisition with the reconstruction to gradually gain confidence.” (NMT#7)

“... training on our own machine, in our daily workplace.” (NMT#5)

The main barriers identified were related to the possible increase in workload that: (i) does not take patient needs into account; (ii) results in burnout situations for both NMT and physicians; and, consequently, (iii) focuses on economic benefit rather than improving patient care or working conditions.

“Then you also have departments that are organised in such a way that, well, there are so many patients to get through in a day. And then, it is fine, he has not moved on to the next one. And in that case, the tool is just there to help you work faster and dumber.” (NMT#4)

Professional resistance and lack of education were also highlighted (Table 3).

“Physicians who do not want to change and do not accept the new reconstructions. They like what they are used to see as images “(NMT#7)

“People who do not understand do not adhere.” (NMT#1)

Discussion

This qualitative study aimed to identify the aspects that can impact the implementation of an AI denoising PET/CT algorithm in clinical practice, based on the representations of NMT from Western-Switzerland, highlighting the barriers and facilitators associated to.

NMT participants' unfamiliarity with AI-based denoising algorithms applied to PET/CT examinations led them to contemplate its potential integration into their practice, envisioning how it would be employed. Despite their lack of AI understanding and formal education on this topic, 50% of the participants could transfer their practical experience obtained in CT and MRI, using denoising AI algorithms such as deep-learning image reconstruction (DLIR)³⁹ for CT and subtleMR for MRI,⁴⁰ to the context of PET/CT examinations. In this study, clinical practice aspects were mentioned more frequently, likely because the sample consisted of NMTs focused on their practice and not very aware of AI.^{20,21,23,41,42}

Participants expect improvements in clinical practice since AI implementations in MI departments can lead to a reduction of acquisition time and improvements in patient comfort.^{24,43,44} While maintaining similar quality and quantitative accuracy, AI-based denoising algorithms have demonstrated to: (i) decrease by 50% the time required for image acquisition^{24,45}; (ii) reduce patient dose/irradiation due to the decrease of 30–50% on the injected radiotracer quantity,^{45–47} with particular impact in paediatric imaging⁴⁶; and (iii) decrease the overall examinations' costs due to the reduction of radiotracer usage, where the costs related to AI implementation and maintenance are offset by the savings from reduced radiotracer use, representing 15–20% of these savings.⁴⁷

These improvements are believed to transform how the PET/CT examinations' workload is organised. Some participants expressed concerns that potential acquisition time reduction could promote

an increase on the workload charging the scheduling to meet the examinations' demand that grows constantly⁴⁸ Conversely, others viewed these adjustments as an opportunity to enhance patient and inter-professional interactions. This ambiguity is reflected in the literature, where some authors argue that an increased workload may not improve service quality or care,²⁷ but rather prioritise⁴⁹ economical profitability.^{20,21,50} In contrast, other studies highlight benefits such as reduced waiting times for an appointment, more time to assist patients in discomfort²⁴ and improved inter-professional communication.^{20–26}

Another identified concern was the fear of possible PET/CT system breakdowns and maintenance challenges. In the NMT perspective, the current high demand on PET/CT examinations is already stressing the IT infrastructure and the added pressure from the AI technical requirements and optimised workload may lead to increased slowdowns on system performance. Though it is expected that existing IT infrastructure can seamlessly integrate AI solutions,⁵¹ it is paramount to access system robustness and reliability to avoid future slowdowns.⁴⁹ Stress tests should be thoroughly performed to determine the stability, reliability, and performance limits of software, hardware, or an entire system under extreme conditions. These tests ensure that the IT infrastructure can maintain functionality and performance during high-stress situations, improving the reliability of the optimised workload and users' satisfaction.^{52,53}

The concerns and fears reported about AI implementation may be related with the participants' low AI literacy level and limited management experience, as highlighted by Jöhnk et al.⁵⁴ These findings stress the importance of management support to promote AI awareness initiatives from the top-down and encouragement of interdisciplinary skills development from the bottom-up. Strategies should include the development of technical skills to upskill MNT knowledge in PET/CT systems, enabling collaboration to adjust workloads and improve service quality and patient care.

Sustainability and role development were also two identified areas discussed by the participants. Sustainability was considered from two perspectives: (i) required energy consumption to run AI algorithms, with potential negative impacts on the environment. Thus, a focus on energy-efficient technologies should be given^{55,56}; (ii) optimisation of radiotracer usage, mitigating possible resources' shortages and radioactive waste reduction. Participants viewed the arrival of AI as an opportunity to embrace new roles in research or advanced practice, a perspective supported by the literature.^{20,21,23}

Participants emphasised facilitators that align with recommendations for AI deployment in clinical practice. Education and training curricula should incorporate AI, with continuing education programmes updating NMT knowledge through a multidisciplinary team approach.^{57,58} Furthermore, AI solutions need to be explainable, interpretable and integrated into workflows.^{40,59} Participants stressed the importance of being involved in the implementation process with practical examples relevant to their specific context, rather than generic cases from manufacturers. They also highlighted the value of having a “local champion”, an NMT with specialised AI knowledge, to support the implementation process.^{29,30} The main barriers identified were increased workload, lack of understanding and training in AI technologies, potentially leading to workplace insecurity or resistance to implementation.^{20,41,42,60,61} These results are related with the AI readiness factors identified by Jöhnk et al. (2020)⁵⁴ - strategic alignment, resources, knowledge, culture, and data - highlighting the need to develop AI awareness, knowledge, and applications in healthcare, specifically for PET/CT examinations, among NMT.

This work has limitations. The small sample size may limit the generalisability of the results. Participants had diverse profiles in

gender, experience, age, and type of workplace, enriching discussions, but none held decision-making roles. The principal investigator's background as an NMT may have influenced data collection and interpretation. Although themes related to clinical practice, workload and knowledge reached information saturation during the second FG, this was not the case for resources.

Future research should include the perspectives of decision-makers and NM physicians, evaluate costs reduction in radiotracer delivery and how these savings translate into lower examination costs for patients or insurance companies. Explanation emerged as a frequently mentioned facilitator, emphasising the need for developing Explainable Artificial Intelligence tailored for MNT.

Conclusion

In conclusion, the implementation of an AI-based denoising algorithm in PET/CT practice requires a careful analysis of the procedures, workload and available resources. It also presents both benefits and challenges, particularly in terms of workflow efficiency and sustainability considerations. Participants expressed varied perspectives and positions, underlining the significance of providing clear explanations, education, and support to ensure successful AI implementation. The study identified several paths to facilitate the adoption of this AI task by NMT into their clinical practice. Inclusion of NMT in this implementation process is one of them and it was considered as crucial for acceptance and efficacy.

Conflict of interest statement

The authors have non-financial interests to disclose.

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