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How artificial intelligence is reshaping the autonomy and boundary work of radiologists. A qualitative study

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Abstract

The application of artificial intelligence (AI) in medical practice is spreading, especially in technologically dense fields such as radiology, which could consequently undergo profound transformations in the near future. This article aims to qualitatively explore the potential influence of AI technologies on the professional identity of radiologists. Drawing on 12 in-depth interviews with a subgroup of radiologists who participated in a larger study, this article investigated (1) whether radiologists perceived AI as a threat to their decision-making autonomy; and (2) how radiologists perceived the future of their profession compared to other health-care professions. The findings revealed that while AI did not generally affect radiologists' decision-making autonomy, it threatened their professional and epistemic authority. Two discursive strategies were identified to explain these findings. The first strategy emphasised radiologists' specific expertise and knowledge that extends beyond interpreting images, a task performed with high accuracy by AI machines. The second strategy underscored the fostering of radiologists' professional prestige through developing expertise in using AI technologies, a skill that would distinguish them from other clinicians who did not pose this knowledge. This study identifies AI machines as status objects and useful tools in performing boundary work in and around the radiological profession.

KEYWORDS
artificial intelligence, boundary work, digital technologies, professional autonomy, professional identity, radiology

INTRODUCTION

There is a growing interest in the potential for integrating artificial intelligence (AI) in health care. AI systems are based on 'an artificial entity capable of solving problems and learning solutions for new problems' (Fazal et al., 2018, p. 246) through a process of deep learning that 'artificially models the neural network of the human brain with a computer' (Fujita, 2020, p. 8). In health care, AI mimics human cognitive functions using complex algorithms to learn features from a large volume of clinical data in order to make real-time inferences on health risks, predict health outcomes, and more generally speaking, assist clinical practice (Jiang et al., 2017).

While the use of AI in health care has been contested (Matheny et al., 2019; Price et al., 2019), one of the clinical areas where AI appears to offer the most promising outcomes is radiology (Lebovitz, 2019; Lebovitz et al., 2021, 2022; Noguerol et al., 2019; Strohm et al., 2020; Yang et al., 2022). There has been a surge in interest regarding the utilisation of AI in radiology over the past decade, as demonstrated by the substantial increase in the number of publications from 100 to 150 previously to 700–800 per year (Pesapane et al., 2018).

Radiology is a clinical field that has historically invested heavily in cutting-edge technological innovation. Since medical images include a certain level of ambiguity, radiologists often struggle to make accurate and complete diagnostic decisions (Lebovitz, 2019). Due to the frequency of diagnostic errors, technologies capable of supporting radiologists in the decision-making process are therefore particularly attractive. Examples of diagnostic technologies integrated in radiology include X-rays from 1896, ultrasound therapy from the late 1920s, thermal imaging and infrared measurement of metabolic heat from the 1950s, computed axial tomography (CAT, or CT) scanning from the 1960s and nuclear magnetic resonance imaging (MRI) from the 1970s (Dolan & Tillack, 2010).

The use of AI tools in radiology began in the 1980s, initially with the development of computer-aided diagnosis (CAD) systems. According to Katzen and Dodelzon (2018, p. 305), 'CAD is an AI technique that utilises pattern recognition to highlight suspicious features on imaging and marks them for the radiologist to review and interpret'. While significant false positive rates remain a limitation of CAD, its accuracy has improved over the last decade and is now routinely used in some fields of radiology like mammography (Fujita, 2020; Katzen & Dodelzon, 2018; Nishikawa & Bae, 2018). The intention behind computerised analysis is to overcome limitations of human visual and cognitive systems by transferring human skills to another entity, reducing the complexity and variability of interpretation, increasing accuracy and dedicating necessary time to diagnosis (Dolan & Tillack, 2010).

Since the 2000s, AI technologies in radiology have undergone a rapid evolution (Hosny et al., 2018; Lebovitz, 2019; Rezazade Mehrizi et al., 2021). The development of a new generation of AI systems 'have the ability to constantly integrate new information' (Katzen & Dodelzon, 2018, p. 305). These systems can exploit increasingly complex deep learning systems based on sophisticated machine-learning algorithms that improve their accuracy and effectiveness over time. That is to say, AI machines continue to learn in a manner comparable to the human brain, but never forget what they have learnt (Fazal et al., 2018).

Developments in AI technologies are promising but they are limited to detecting and diagnosing abnormalities, which include disease segmentation, diagnosis and staging. Several studies highlight how AI can improve the reliability of prognosis and diagnosis, thereby increasing the efficiency and accuracy of imaging interpretation, reducing human error, speeding up workflow, and improving radiologists' quality of work (Fazal et al., 2018; Hosny et al., 2018; Lebovitz et al., 2022; Rubin, 2019; Thrall et al., 2018). To exemplify, AI machines can support radiologists in making predictions by monitoring changes in clinical parameters over time and through relevant contributions to radiomics (*the clinical discipline that aims to extract a large number of quantitative features from medical images using data characterisation algorithms*) (Fujita, 2020; Parekh & Jacobs, 2019). Furthermore, some scholars have reported a growing interest in using AI to restructure the administrative workflow of radiologists (Kapoor et al., 2020; Rezazade Mehrizi et al., 2021). AI can offer support with scheduling, prioritising seriously ill patients, reporting activities and offering new opportunities for accomplishing tasks related to the identification of suspicious or positive cases (Thrall et al., 2018).

Driven by the potential of AI in radiology and the promises associated with its future developments, a number of studies have sparked a debate regarding its impact on radiology as a profession. Some have argued that AI Machines have the potential to cause significant disruptions to the practice of radiology (Recht et al., 2020) and also 'transform professional relationships, patient engagement, knowledge hierarchy, and the labour market.' (Geis et al., 2019, p. 436). The increasing spread of deep learning technologies has fuelled the discourse of radiologists' replacement by AI machines (Chockley & Emanuel, 2016; El Hajjam, 2020; Nishikawa & Bae, 2018; Obermeyer & Emanuel, 2016; Strohm et al., 2020). This is because 'by transferring knowledge and judgement to a computer, the authority and intellectual territory of radiologists were threatened' (Dolan & Tillack, 2010, p. 231). The arguments in favour of this thesis are based on the following two assumptions: firstly, that machine learning can handle significantly more complex data sets than human beings; secondly, the progressive improvement of deep learning technologies allows AI systems to make autonomous decisions, effectively, making the radiologist's work obsolete. However, the debate on the risk of radiologists' replacement by AI is still controversial as some scholars consider this risk to be very concrete, while others believe it is unlikely (Chockley & Emanuel, 2016; Doi, 2007; Hosny et al., 2018; Recht & Bryan, 2017; Rubin, 2019; Strohm et al., 2020).

Whilst there has been research on the possible impact of AI in health care (Matheny et al., 2019), the relationship between AI technologies and radiologists' identities has not been examined sociologically. To address this gap, this study investigates two primary aspects. Firstly, it explores whether radiologists consider AI as a threat to their decision-making autonomy. Secondly, it examines how radiologists perceive the future of their profession with regards to their professional and epistemic authority, as well as the demarcation between themselves and other health professionals in terms of boundary work.

THEORETICAL FRAMEWORK

Our theoretical underpinnings stem from social science studies exploring issues related to professionalism among physicians, with a specific focus on the concepts of professional autonomy and boundary work. In the sociology of professions, an individual's capacity to exercise autonomy and have control over their work, is a key aspect of professional work (Abbott, 1988; Freidson, 1986). Moreover, autonomy distinguishes one profession from another. Professional autonomy is therefore the degree of legitimate control that the members of an occupation exercise over the organisation, as well as the terms of their work. In clinical fields, professional autonomy translates into clinical autonomy, which refers to the ability of doctors to make clinical decisions without being limited by external factors such as organisational procedures, financial concerns, performance measurement systems or managerial control (Salvatore et al., 2018).

For the last 5 decades, there has been an ongoing debate about the erosion of clinical autonomy, which is often attributed to the decline of medical dominance and de-professionalisation (Larkin, 1983; Navarro, 1988; Tousijn, 2002). Some scholars have argued that professional autonomy in clinical settings, a critical aspect of medical dominance, has been challenged by various processes such as greater accountability (through litigation and self-regulation) and evidence-based practice (Bury & Taylor, 2008). However, Eliot Freidson, a leading scholar of the medical profession, has argued that the decline of professional autonomy among doctors over time should be examined from different perspectives (Freidson, 1984). In his view, professionalism is traditionally characterised by two different levels of autonomy: individual and collective. At the individual level, physicians have been losing autonomy since the 1960s mainly due to greater external controls, such as those imposed at organisational and bureaucratic levels. Meanwhile at the collective level, there have been attempts to increase the autonomy of physicians through processes of stratification. This stratification has resulted in a hierarchical distinction between physician–administrators and the physician–researchers, with the former having greater autonomy. According to Freidson (1984) therefore, the erosion of individual clinical autonomy is countered by an increased promotion of autonomy at the collective level by the medical profession as a whole. In Italy, the decline of medical dominance seems to be only partial in that it affects certain dimensions while not leading to the total disappearance of medical power (Tousijn, 2002). Collective autonomy in this country seems to be achieved through self-regulation, specifically through a frequent renewal of ethical codes and the production of guidelines.

Professions, however, have unique features beyond autonomy, such as distinct knowledge and expertise (Saks, 2012), which they use to compete for control over their respective field, thus ensuring exclusive practice. This leads to the introduction of boundary work as another concept in our theoretical framework. 'Boundary work' can simply be conceptualised as an active classification process through which 'people bring some social objects inside a category or concept whereas they push others out of the definitional frame of this category or concept' (Åkerström, 2002, p. 517). The literature on this concept is further divided into external boundaries or internal boundaries. While the former calls upon the attempts of researchers to separate science from non-science (Gieryn, 1983; Gómez-Morales, 2015), the latter focuses on internal demarcation work between or within different disciplines (Amsterdamska, 2005). On that note, Amsterdamska (2005, p. 20) states that, 'the establishment of such internal boundaries creates the need to emphasise both the distinctiveness of a field of research and, simultaneously, its conformity with the prevailing, though changeable, standards or markers of scientificity'. Internal boundary work is therefore flexible and subject to change.

The growing presence of multidisciplinary teams in the clinical setting has raised an interesting debate on how these boundaries are negotiated and reconfigured (Liberati et al., 2016). Some studies have already explored how scientists use internal boundary work to secure their cultural authority (Burri, 2008; Fournie, 2002). Fournier (2002) has for example, argued that boundary work depends on two processes: the first is the constitution of an independent and self-contained field of knowledge which provides a foundation for professional authority and exclusivity; the second concerns the division of labour for establishing and maintaining boundaries between the professions.

Social scientists have demonstrated how the introduction of new medical technologies impacts the overall organisation of health-care work and health professionals' identities (Lindberg et al., 2017). One sociological theory, known as the 'technology-in-practice' approach which has caught the interest of many scholars (Berg, 1997; Timmermans & Berg, 2003a), offers a framework for investigating these phenomena. This approach assumes a dialectical relationship between the technologies and their users that is between human and non-human actors (Latour, 2005). By adopting this theoretical approach, Berg (1997) demonstrated that the decision-support techniques based on new technologies (computer-based support systems, protocols and clinical decision analysis) have transformed medical practices and encouraged a continuous process of negotiation between human and non-human actors. Due to this, decision support systems were frequently modified once adopted, often considerably challenging the original 'scientific' thought processes of their algorithms. Subsequent studies align with Berg's findings, demonstrating how health-care professionals still possess significant decision-making power and professional autonomy despite the push for standardisation (Timmermans & Almeling, 2009). These studies also examine the adoption of technologies that aid decision-making, such as those in the field of Evidence-based Medicine or Automated Decision-Making (ADM) (Bergquist & Rolandsson, 2022; Timmermans & Berg, 2003b; Timmermans & Kolker, 2004). Furthermore, Peiris et al. (2011) have revealed that social and moral values impact the scientific decision-making process when using EDS (electronic decision support) for managing heart disease among Australian GPs. Additionally, social scientists have demonstrated that medical technologies affect boundary work. For example, Håland (2012) showed that the electronic patient record (EPR) affected the boundary work and professional identity of doctors and nurses by changing their work distribution.

We hypothesise that AI can impact the radiology profession in two ways: through professional autonomy and boundary work. AI systems may reduce radiologists' decision-making autonomy, limiting their control over tasks. Additionally, the introduction of AI could blur professional boundaries, potentially providing other health professionals with tools to perform tasks that were previously unique to radiologists. We argue that these processes could prompt radiologists to reassess and redefine the boundaries of their professional domain and their jurisdiction over a specific area of medical knowledge. As such, we adopted the concept of boundary work to investigate the discursive strategies performed by participants as they discuss AI technologies in relation to their identity and autonomy as radiologists.

METHODS

Our analysis drew on 12 in-depth interviews with radiologists. These were conducted as part of a broader project aimed at exploring how AI affects the health-care system in Italy, with a specific focus on health professions and the relationship between health-care professionals and patients.

Participants were recruited following a selection criteria that required them to be working in a radiology department where AI technologies were being tested and used. Following this, purposive sampling was used to recruit a heterogeneous sample of radiologists from various health-care institutions (public vs. private hospital), ages (under vs. over 50 years old.), genders (male vs. female) and geographic areas (Northern, Central and Southern Italy). Regarding the gender balance, we had difficulty recruiting female radiologists who worked in a radiology department where AI technologies were tested and used due to the greater presence of male radiologists in this field. The same applies to the geographical criterion: Southern regions are underrepresented in our sample because most of the centres, researching and testing AI tools, are located in the North and Centre of the country. The team of researchers from the School of Medicine who are involved in the larger project supported recruitment by identifying experts on AI in radiology at the national level. Interviews were conducted until saturation was reached, meaning that no additional insights were found.

Potential participants were provided with a brief description of the project's aims and invited to participate by email. If they agreed to participate, the interviews were scheduled. Participants provided informed verbal consent before interviews commenced. All interviews were conducted online in Italian by two separate researchers. The interviews lasted an average of 60 min and were audio-recorded. Data were collected between July and December 2021. Interview topics were formulated with the aim of investigating the research objectives and establishing a shared and consistent approach to gathering the data (Patton, 2002). The interviewers used the same semi-structured background questions that addressed (1) educational background and professional experience; (2) experience with and perspective on AI; (3) how AI is affecting/will affect training, clinical practice and inter-professional collaboration; (4) how AI is influencing/will influence the relationship between radiologists and patients in terms of trust, communication and informed consent; (5) perceptions on responsibility, autonomy and professional identity as practitioners; and (6) impact of the COVID-19 pandemic on AI systems in radiology. This article analyses the findings from questions 2, 3 and 5.

Field notes were collected during interviews to record observations and non-verbal data that the medium (video call) allowed to gather, as well as additional information concerning the context and background of the interview (e.g.: postponements or difficulties in scheduling the meeting; external interruptions or technical issues during the interview; overall climate of the conversation and off-the-record exchanges between interviewer and interviewee).

Interviews were transcribed verbatim by the research team and later imported to NVivo12 for data management, coding and analysis. For each interview, a memo file was drawn up containing field notes and an annotated summary of the most relevant points that emerged. The coding procedure followed the template analysis approach (King, 2012) which began by the creation of deductive codes based on the research questions and interview guide, followed by the generation of inductive codes. An author (ER) prepared the first version of the template. Additional codes were developed throughout the analysis process, and the template was modified accordingly.

To measure the inter-rater reliability and degree of agreement for coding between the two analysts, a comparison query with NVivo12 was run. The k coefficient was >0.5 for each code, and the degree of convergence was between 89.6% and 100%. In order to improve the robustness of the analysis, discussions were held between the researchers about codes with a lower degree of agreement. Once the interviews had been coded, a more focused analysis was conducted to identify themes and extract illustrative quotations. The final interpretive process involved identifying associations, patterns and explanations within the data. The analysis was performed in Italian to avoid language barrier limitations, and quotations were translated into English for presentation in this article. The subsequent section illustrates the main findings identified through the analysis process.

Participants

A total of 12 individuals were interviewed, 11 men and one woman. The age of participants ranged from 36 to 64 years with the mean age being 45 and 67. Five radiologists were employed

TABLE 1 Characteristics of participants.

	Age	Gender	Geographical area	Organisation
Radiologist 1	63	M	North	Private
Radiologist 2	34	M	Centre	Private
Radiologist 3	42	M	North	Private
Radiologist 4	33	M	North	Private
Radiologist 5	34	M	Centre	Private
Radiologist 6	48	M	North	Public
Radiologist 7	55	M	Centre	Public
Radiologist 8	46	M	Centre	Public
Radiologist 9	59	M	Centre	Public
Radiologist 10	35	M	Centre	Private
Radiologist 11	50	F	Centre	Private
Radiologist 12	49	M	South	Public

in public hospitals and seven in private institutions. The demographic and professional characteristics of the participants are summarised in Table 1.

FINDINGS

This section presents the findings corresponding to questions 2, 3 and 5 of the interview guide exploring 2) experience with and perspective on AI; 3) how AI is affecting/will affect training, clinical practice and inter-professional collaboration; and 5) perceptions on responsibility, autonomy and professional identity as practitioners. These findings are organised under the following themes: 'It will take time', representing radiologist's attitudes towards AI and their perceptions about its impact in radiology (question 2); 'This is what being a radiologist means' corresponding to the impact of AI on radiologists' professional identity and autonomy (question 3); 'Don't be a DIY diagnostician!' addressing how AI (is expected to) influence(s) inter-professional collaboration and boundary work (question 5).

'It will take time': Radiologist's attitudes towards AI and their perceptions about its impact in radiology

The interviewed radiologists were generally optimistic towards the development of AI technologies and recognised the revolutionary scope of deep learning systems applied to radiology. Deep learning systems were defined by a participant as a 'Copernican revolution' in the field. A number of respondents noted that AI is a sort of umbrella concept that includes significantly different technologies covering the detection of abnormalities, disease diagnosis, post-processing images, the Internet of Things and administrative workflow. Although there is great excitement in this field, it is noteworthy to mention that the majority of AI machines using deep learning technologies are currently undergoing testing and validation by certification bodies. Hence, the current phase is mainly characterised by research and experimentation while its use in clinical practice is still not widespread. For example, one participant commented:

> So the topic in my opinion is a bit premature. (…) Right now there is no software in clinical practice, they are not included in the guidelines, and so let's say this is a question that we have difficulty answering. What we are certainly trying to do is talk about it to prepare the radiology population.
>
> (Radiologist 8)

One of the areas of AI perceived as very promising by the interviewees is predictive medicine aimed at evaluating patient survival rates or forecasting the evolution of a disease (e.g., tumours) through the development of models. Other important developments were also expected in the area of personalised medicine to address the prediction of susceptibility to disease, customising disease-prevention strategies and prescribing more effective drugs.

The most commonly anticipated benefits of future AI tool developments concerned enhanced diagnostic speed, improved detection and diagnostic accuracy, increased reliability, reduced diagnostic error rates compared to AI-unassisted practices, decision-making support and the potential to make future predictions. Here, we discuss the perceived effects of AI on time and workflow.

Time

While discussing the potential benefits of AI, many of the participants' comments focused on time-saving and gains in labour efficiency. The interviewees expressed hope that the time saved could be used to do more research, take charge of multiple clinical cases, discuss critical cases with colleagues and dedicate more time to relationships with patients. Nevertheless, there were some hesitations among radiologists about the time-saving potential of deep learning AI technologies due to two factors presented in the following.

First, the process of training radiologists to use AI technologies effectively and facilitating the learning of AI machines can be time-consuming:

> Well in the beginning certainly there is an increase in time, because I have to learn, as you said, how the system works, learn to interpret [it], learn to believe the system, compare it[s results] with my knowledge.
>
> (Radiologist 9)

> It also takes time to feed the system, I guess. In the initial stages, in the development, I guess there is also a time. Like when the… Let's say the voice message, you had to do the cell phone training with your voice—which you don't do anymore—eh in the beginning… it takes time to set up what you're given for how you need it. (…) Anyway to get yourself used to thinking in a different way. Then afterwards instead I think it reduces, reduces, reduces notably, significantly your working time.
>
> (Radiologist 9)

Second, some participants hypothesised that the utilisation of these technologies would add to the complexity of decisions, thereby increasing the working time required. In fact, the integration of AI technology into the radiologist's workflow was expected to necessitate an overall redistribution of work time:

> It was thought that increasing the speed of machines increased the ability to do examinations over time. Now in my view, and of many who think like me, this is where you have to distinguish between machine-time and doctor-time (...) With a machine I will always be faster and take less time? (...) No, because it increases the complexity of the decisions that I have to make.
>
> (Radiologist 8)

Workflow

Another identified advantage of AI was its potential to redefine workflow, especially for the identification of severe cases that need prioritised examination.

Although the respondents mainly identified benefits related to AI, they also discussed possible disadvantages such as the lack of system certification; the cost increase associated with designing, purchasing and updating AI machines; and the problem of the decision opacity (known in the literature as the 'black box' issue, Lebovitz et al., 2022).

Several participants also pointed to a possible increase in diagnostic errors resulting from an excessive confidence in AI by radiologists:

> I don't know, maybe relying too much on artificial intelligence systems maybe you might miss some things, mmmh because you trust the machine too much.
>
> (Radiologist 11)

> The final decision, the final diagnostic definition can be influenced.
>
> (Radiologist 7)

Finally, some participants expressed concerns about the future of the radiology profession, which will be presented under the subsequent subheading.

'This is what being a radiologist means': Impact of AI on radiologists' professional identity and autonomy

When asked to identify the main impact of AI technologies on the radiology profession in the future, most respondents did not anticipate learning systems to pose a threat to their professional autonomy. That is to say the majority of the participants stated that their autonomy was safeguarded from AI technologies. The interviewees expressed minimal concern about the risk of an 'automation bias', or the risk of humans starting to rely entirely on the work of machines rather than applying their own critical judgement and examination. As depicted below, despite the significant improvement in the accuracy of AI systems, they cannot be deemed completely reliable as they are incapable of connecting the data to the patient's medical history.

> Because it's obvious that there are a whole series of conditions that artificial intelligence cannot pre-analyse and deem as assessment criteria, for example, if a patient

> had lung surgery 10 years ago, it's a normal x-ray picture for someone who has had lung surgery, but artificial intelligence will deem it pathological because there's something it sees that shouldn't be there, no?
>
> (Radiologist 6)

In this context, the discussion revolved around the impact of AI as an aid and its effect on professional autonomy.

AI as an aid

Participants primarily conceptualised AI in terms of an aiding tool that could help them accomplish their tasks more quickly while also reducing the likelihood of errors. AI technologies were seen as a decision-making tool, with the AI machine serving as only one of the possible criteria that informs the radiologist's final decision. In fact, the clinical decision cannot disregard the overall evaluation of the patient's clinical history, a domain which is only managed by the human professional. Furthermore, the professional experience of the radiologist represents a crucial component that comes into play in making clinical decisions. These findings are illustrated by the following interview excerpts:

> The radiologist does not rely on the machine in a, shall we say, supine way. In the interpretation of the images, if you like, it's kind of our companion, our second reader.
>
> (Radiologist 7)

> I don't see software as my antagonist, I see it as a support, as something that can help me. [...] I reason with my head, however, maybe the computer can open a perspective for me that at that moment, either because I am tired or because I have had little experience in that field or because I am distracted, maybe I did not think that those characteristics of that lesion could be related to a type of tumour.
>
> (Radiologist 9)

> The machine can suggest you some... Some possible options, but then because there are so many options, it's not like there's only one option, I think the doctor intervenes in the decision. That is, the decision that... It's made by experience, it's also made by the individual case, it's made by so many things.
>
> (Radiologist 11)

AI and professional autonomy

In line with this view, participants confidently stated that evaluation and decision-making remained the responsibility of the radiologist who wrote the clinical reports. A recurring metaphor among interviewees was the automatic driving function of a car, which assists the driver but does not replace them.

> Autonomy is complete in the sense that, I repeat, the moment I sign I take full responsibility for it meaning I put a name and a surname at the bottom of a diagnostic

> conclusion and I am accountable for that, in front of the patient, in front of the judges, in front of the lawyers, in front of everything that clearly follows from that so I can never make the excuse: "But, the computer told me".
>
> (Radiologist 7)

> In my opinion, I always see artificial intelligence as something in addition ... To what I can do. It's not that because there is an automatic transmission, we have stopped driving the car. It's that you don't shift anymore, but you keep driving the car.
>
> (Radiologist 11)

While most participants did not find AI to affect their professional autonomy, one participant believed that it did, but that it was trade-off for the accuracy offered by AI:

> When another medium processes the data, your autonomy is reduced, it's like that, however let's say if the reduction in autonomy leads to a reduction in the error rate, it's like that, you have to accept it.
>
> (Radiologist 2)

Almost none of the participants feared AI technologies posing a threat to their work autonomy or leading to their professional replacement in the near future. The most common justification for this was closely linked to the role of the radiologist who, in the view of the interviewees, did more than mere reporting activities. In other words, the radiologist should not be considered a technician, a sort of 'reporting machine', but a doctor with an expertise in the broader clinical field. Thus, to be a good doctor, it is important to make good diagnoses and have good relationships with patients. In this future scenario, AI machines represent fundamental support, particularly for the simplest and most routine tasks. The following quotes illustrate this

> The radiologist will never be replaced but will be precisely, as mentioned, responsible for the more challenging tasks, [...] time is also important and therefore Artificial Intelligence saves us time and we can become less technocratic, technological and take care of patients more which is always one of the problems radiologists have, that they are always away from the patients.
>
> (Radiologist 1)

> It is then not simply looking at stickers and saying: "I see a dot rather than a line rather than I see some strange thing", but interpreting the signs that you see, tracing them back to a clear pattern of pathology and then drawing diagnostic conclusions, this is what being a radiologist means, it does not mean describing what I see on a monitor but knowing how to make diagnoses with what I see on a monitor which is a totally different concept.
>
> (Radiologist 7)

An important observation from these interview excerpts is how the potential threat posed by AI technologies is somehow reversed and exploited to confirm and re-establish the identity of the radiological field (e.g., as an innovative and future-oriented discipline) and to even strengthen its reputation. Through the process of boundary work, which draws the limits and characteristics of the radiology profession as they are stated (i.e., 'this is what being a radiologist means'), the risk of losing autonomy and eventually being replaced is converted into an opportunity of being closer to the patients. AI technologies could assist menial and time-consuming tasks, enabling radiologist to focus more on building relationships with their patients.

'Don't be a DIY diagnostician!': How AI (is expected to) influence(s) interprofessional collaboration and boundary work

Among those participants who explicitly described using and experimenting with AI in their clinical practice, a frequently emerging theme concerned AI's impact on inter-professional collaboration. The findings of our study suggest that the spread of deep learning systems in radiology could both create new forms of collaboration and transform existing ones.

New inter-professional collaborations

A number of participants recognised the ability of AI to expand teamwork with non-clinical professionals. These include computer scientists and statisticians who are involved in the design and management of IT systems and in the analysis of predictive models. The inter-professional collaboration reported was primarily characterised by a distinct division of tasks, roles and competences without challenging the professional boundaries or authority of radiologists.

> [I make] reference to our group, for example, which is run by me, who is a radiologist, then there is a statistician, there is … There are several physicists, there is a mathematician … There are oncologists. So, there are a number of professional figures, everyone, clearly, contributes their part.
>
> (Radiologist 12)

Transformation of professional boundaries

Regarding the transformation of current collaborative practices with other health professionals, the results highlight that respondents shared some concerns about the possible blurring of professional boundaries in the future. Namely, they feared that other clinical professionals may improvise radiologists' work by using AI systems to detect and diagnose, erroneously assuming that the work of the AI machine can substitute that of the radiologist. For example,

> I recommended once again to the clinician not to be, how should I say, the "DIY-radiologist," the "DIY-diagnostic," that is, not to go and look at the images and interpret the images independently but always to do so in light of what is written in the report.
>
> (Radiologist 7)

The excerpt above exemplifies one of the most important findings from our study. On the one hand, the interviewees thought that AI systems would not impinge on their work autonomy. On the other hand, they feared that AI could threaten their professional boundaries in terms of epistemic authority, particularly in relation to those clinicians who usually read radiological reports in their routine clinical practice.

The apprehension of reconfiguring work boundaries with other health professionals, stimulated interviewees to protect and reaffirm their professional boundaries. This was mainly accomplished through two discursive strategies. First, they stressed their specific expertise as doctors involved in the overall interpretation of clinical data and not merely as technicians engaged in reporting. Second, participants emphasised how the spread of AI systems required radiologists to develop new skills that could reconfigure their professional identity and increase the prestige and reputation of their role.

Finally, some participants anticipated that the advancement of deep learning systems would lead to the creation of new boundaries within the radiology profession, widening the divide between AI users and nonusers and thereby enhancing the reputation and status of the former. Advocates of this optimistic stance emphasised that AI can present an opportunity for the profession rather than a threat, as proficiency in deep learning technologies could demarcate 'specialist' from 'generalist' radiologists.

> Perhaps at first it can only be a good thing because the use of these technologies can only be boasted, that is, working in a centre that allows you to do re-elaborations to acquire even functional data that other machines do not allow you to do can only be a boast.
>
> (Radiologist 2)

DISCUSSION

Similar to findings by Strohm et al. (2020), our findings suggest that radiologists' views on the increasing use of AI systems in their clinical field range from enthusiastic to fearful, with most participants in our study expressing a positive outlook. This positive attitude was primarily due to the shared expectation that AI tools could lessen their workload, particularly for mundane and administrative tasks. As pointed out by other scholars (Lebovitz, 2019; Simon et al., 2020), radiologists are often overwhelmed and suffer from burn-out and time pressure in their organisational context. The participants in our study believed that the time saved by AI tools could be used to focus on relationships with their patients and engage in clinical research. The use of AI for repetitive and time-consuming tasks could also improve 'the purpose and sense of satisfaction of radiologists themselves as well' (Recht et al., 2020, p. 2).

While some scholars have defined the work of the radiologist as complex, solitary and far from the patient (Topol, 2019), others have highlighted how most radiologists regularly interact face to face with patients (European Society of Radiology, 2020). The results of our study are more in line with the latter definition of radiologists' work, with many interviewees expressing widespread hope that the development of AI systems could give them more time to devote to their relationships with patients, a finding similar to other studies on AI in radiology (Pesapane et al., 2018; Recht & Bryan, 2017). This is particularly stimulating for its practical and ethical implications as it seems to suggest that the adoption of AI systems does not make the clinical work of radiologists more impersonal, but on the contrary could improve the doctor–patient relationship and promote a more patient-centred care.

Previous research indicates that since radiologists do not generally trust AI to make decisions autonomously, AI does not pose the threat of replacing them professionally (Chockley &

Emanuel, 2016; Hosny et al., 2018; Recht & Bryan, 2017; Rubin, 2019; Strohm et al., 2020). The future of this field is instead depicted as human actors and AI machines working together as co-pilots (Waymel et al., 2019; Yang et al., 2022), collaborative intelligences (Epstein, 2015; Paul et al., 2018; Wilson & Daugherty, 2018), and as a 'diagnostic team' (Jorritsma et al., 2015), though the main responsibility will remain with radiologists (Geis et al., 2019; Lebovitz et al., 2022). Similarly, our findings indicate that the computer's capability is combined with the radiologist's competence. AI devices used for diagnosis and detection often serve the purpose of a second opinion or a 'second pair of eyes' (Rubin, 2019). When using CAD, for example, radiologists are influenced by the results it generates, but simultaneously utilise their expertise to identify the clinical 'significance' of the points highlighted by CAD (Dolan & Tillack, 2010). This is also true for more cutting-edge AI technology, such as deep learning systems and algorithms-based tools, where the clinical report is the product of a careful negotiation process between the radiologist's clinical experience and the assessment of AI machines. According to Maiers (2017), clinicians' decision-making processes are affected not only by predictive algorithms but also by two interpretive processes: 'conditioned reading'—'the processes through which users of data-driven technology temper, filter, discount, or place trust in its output' (p. 923); and 'accumulative reading'—'the process by which data-driven technology is layered upon other information and sometimes used to assess the meaning of other information' (p. 924).

Despite the generally positive attitude of radiologists in this study towards AI's application in radiology, some expressed concerns about its future influence on their profession. These respondents were sceptical about whether incorporating AI into routine clinical practice would actually save time or result in a re-distribution of work (Vikkelsø, 2005). The reasons described for this mirrored those found by other scholars, such as the initial investment of time required to use the AI machine (Neri et al., 2020) and the additional time needed to reconcile the AI knowledge claims and the clinical evaluation (Lebovitz et al., 2022). This disjuncture between human and non-human work due to the introduction of algorithms to support decision-making in health care has been described as 'algorithmic work' by Bailey et al. (2020).

While attitudes towards the adoption of technology in radiology were often conceptualised as an 'active or passive' binary among the participants, studies show that in practice, this relationship is more complex (Noguerol et al., 2019; Timmermans & Berg, 2003b). This dichotomous attitude among radiologists may have been shaped by their inexperience with and speculations about the use of AI technology.

Other participants explained that while the spread of AI in radiology was not a threat to their professional autonomy, they feared that it would cause a loss of authority to other clinical professionals. This could also result in the blurring of professional boundaries in the medical field, due to the risk that other health professionals may improvise radiologists' work with the mistaken belief that AI machines could replace them. To avoid this risk, the radiologists interviewed adopted two discursive strategies, which are described next.

The first strategy focused on defending the radiologist's identity by stressing their specific expertise and field of knowledge (Fournier, 2002). This strategy is exemplified in the radiological literature itself, 'the radiologist, as a physician, is much more than simply an interpreter of images. The duties of a practising radiologist also include communication of findings, quality assurance, quality improvement, education, interventional radiology procedures, policymaking, and many more tasks that cannot be performed by computer programs' (Pesapane et al., 2018, p. 751).

The second strategy aimed to establish that the advancement of AI would foster the prestige of radiologists by equipping them with new skills through specialised training, thus creating a division between radiologists who use AI technologies and those who do not. This strategy reflects the theory of Fournier (2002) which, as illustrated in the theoretical framework, argues that professionals defend their work boundaries by reinforcing an independent and self-contained field of knowledge, over which they claim to retain a monopoly as unique legitimate repositories of that expertise. Furthermore, a connection can be drawn to Burri's (2008) work which demonstrated how the spread of visualisation technologies contributed to reconfiguring the disciplinary identity of radiologists and transforming their epistemic authority, increasing their degree of prestige and honour. In other words, AI machines and the knowledge required to manage them can be interpreted as status objects which can increase the symbolic capital of radiologists who operate them. Similarly, Burri (2008) argued that 'imaging practices can be read as boundary work and as distinction practices aimed at achieving symbolic capital in the academic and professional field. The acquired prestige serves also to re-establish the individual professional identity of radiologists' (Burri, 2008, p. 42). While she looked at the process of boundary work in radiology from an external perspective, our study takes an internal perspective, specifically focusing on how AI technologies intervene in the internal boundaries of the radiology profession.

CONCLUSIONS

This article has explored radiologists' perspectives on the present and future impact of AI systems on the field of radiology, with a specific focus on their beliefs about how AI machines may impact their work autonomy and professional boundaries. The findings suggest that AI systems have the potential to significantly impact not only the way radiology will be practised but also the professional status of radiologists in the near future. These results are consistent with other studies that have demonstrated the need for radiologists to reframe their professional identity as a consequence of the introduction of AI applications (Strohm et al., 2020).

While the influence of AI technologies in radiology cannot be ignored, the findings of this study suggest that AI should serve to aid and not replace radiologists. However, even if work autonomy concerning the decision-making process was not posed as a concern, the radiologists interviewed were apprehensive about the respect for their professional and epistemic authority. In order to protect their authority, radiologists emphasised their specific clinical identity and underlined the importance of training aimed at developing specific skills for the use of AI technologies. In fact, if future scenarios include the use of AI technologies in routine clinical practices performed by radiologists, radiologists must be trained to improve their competence in AI use. During their training, radiologists should be made aware that they hold the ultimate decision-making responsibility, notwithstanding the assistance of AI machines.

This study offers valuable insights into the attitudes of radiologists towards AI technologies and makes two important contributions to health and medical sociology. First, our research suggests that radiologists feel threatened, not so much by AI machines but rather by clinical colleagues who might misuse AI. Second, it illustrates the main strategies used by radiologists to maintain their professional boundaries. In addition, this study has important implications for future research. Subsequent research should explore whether the fears of radiologists regarding their loss of authority due to the use of AI technologies by non-radiology clinical professionals are well-founded and if so, what medical implications it could have. Future studies should also explore how the political and organisational contexts surround the process of AI technology adoption among radiologists and how it affects their identity. This could shed light on how policymakers and health-care managers can shape the autonomy and boundary work of radiologists.

Although this research produced interesting results, several methodological limitations should be considered when interpreting its findings. First, we recruited radiologists who had had some experience with using AI. The sample could therefore be biased towards individuals with a particular interest and a more positive attitude towards AI technologies. A second limitation was the difficulty in recruiting radiologists who were particularly sceptical about the future consequences of AI technologies. This could have introduced biases due to the homogeneity of radiologists in terms of positive attitude. Third, we failed to balance gender among respondents, and this was mainly due to the gender imbalance in this clinical field as other researchers have also highlighted (Slanetz et al., 2021). Fourth, although meaningful reflections were obtained and thematic saturation occurred, the number of participants was relatively small. Lastly, our study focuses on the Italian context, and some results could be linked to the cultural and organisational specificities of our country. These limitations should be taken into consideration in future research.

AUTHOR CONTRIBUTIONS

Both authors conducted and analysed the interviews. Linda Lombi wrote the first draft of the manuscript. All authors read, revised and approved the final manuscript.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study can be obtained from the corresponding author upon a reasonable request.

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