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Research article

Beyond the Screen: Development and Preliminary Validation of an Instrument to Quantify Radiologists' Attitudes Toward Artificial Intelligence Integration in Practice

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Abstract: Artificial intelligence (AI) has achieved broad penetration across various sectors, notably within healthcare. Specifically in medical imaging, the emphasis is currently on developing and rigorously validating AI algorithms to augment diagnostic accuracy and streamline clinical efficiencies. This technological shift, however, simultaneously generates substantial questions and fuels professional debate among radiologists, thereby influencing their evolving perception of AI. The aim of our study was to validate the Radiologist Doctors' Perceptions of Artificial Intelligence Questionnaire (RDPAIQ), a novel instrument designed to assess the attitudes towards the AI implementation in radiological practice. We developed a 24-item questionnaire structured into five sections: (1) Demographics factors, (2) Experience with technology and AI, (3) Perception of AI-assisted radiological diagnosis, (4) Radiologist-AI interaction, and (5) Challenges, ethics, and confidentiality in AI integration into radiological practice. The questionnaire was administered to a cohort of 74 radiologists. The RDPAIQ showed a Cronbach's alpha of 0.718 and factor analysis suitability (Bartlett's χ^2 = 39.6718, $p < 0.001$), validating its utility in clinical AI readiness assessment. As a summary, the RDPAIQ is a reliable and valid instrument for exploring the radiologists' perspectives on AI integration in diagnostic imaging. Understanding these perceptions is vital for mitigating potential biases and ethical concerns associated with AI deployment, ensuring an equitable and responsible clinical application.

Keywords: questionnaire, validation process, perceptions, artificial intelligence, radiology, medical imaging, clinical integration

1. Introduction

Artificial intelligence (AI) is a computer science discipline dedicated to developing systems that emulate cognitive functions associated with human intelligence, including learning, creativity, analytical reasoning, and decision-making. The field of AI comprises multiple specialized subdomains, each targeting specific dimensions of intelligent behavior or particular problem-solving domains. Prominent examples include deep learning (DL) for image recognition, machine learning (ML) for data-driven prediction, and natural language processing (NLP) for human-language understanding and generation [1-4].

Nowadays, AI demonstrates the capacity to process and analyze extensive volumes of data – encompassing imaging, electronic records, and ancillary information – enabling the identification of subtle patterns and correlations beyond the scope of human analytical capabilities [5-6]. Further, AI has expanded into many areas, with healthcare being no exception. In medical imaging, researchers are increasingly developing and training AI algorithms to enhance diagnostic accuracy and improve clinical outcomes [7-9].

Notably, extensive research demonstrates the capabilities and promising performance of AI algorithms in radiology. AI-based models are transforming image acquisition, reconstruction, and interpretation processes, enhancing both efficiency and accuracy [10]. In particular, DL-based systems have achieved diagnostic performance comparable to that of board-certified radiologists across multiple imaging modalities. Recent evidence demonstrates their efficacy in detecting lung nodules on chest computed tomography (CT) scans, mammography screening, and acute stroke diagnosis using CT or magnetic resonance imaging (MRI) [11-13].

However, this emerging technology remains under development, with comprehensive large-scale studies – particularly those assessing long-term outcomes and involving substantial patient cohorts – yet to be conducted [14]. Moreover, healthcare professionals rightly worry about AI's clinical integration, as emerging evidence suggests certain diagnostic tasks may become automated, potentially endangering traditional radiology roles. This technological advancement raises significant questions and sparks debates among radiologists, shaping their perspectives on AI. Thus, the role of AI in diagnostic imaging is not well defined in the current radiological practice [15-17]. Also, integrating AI into healthcare presents several challenges, including data privacy concerns and the need for robust validation and regulatory frameworks [18].

Thus, a critical yet underexplored barrier to AI adoption is radiologists' perceptions – encompassing trust, perceived utility, ethical reservations, and readiness to integrate AI into daily practice (Figure 1) [19]. While some studies suggest that radiologists view AI as a supportive tool rather than a replacement [20], others report skepticism due to lack of transparency and liability concerns [21]. Understanding these perceptions is essential for designing targeted training programs, improving human-AI collaboration, and guiding policy decisions [22-24].

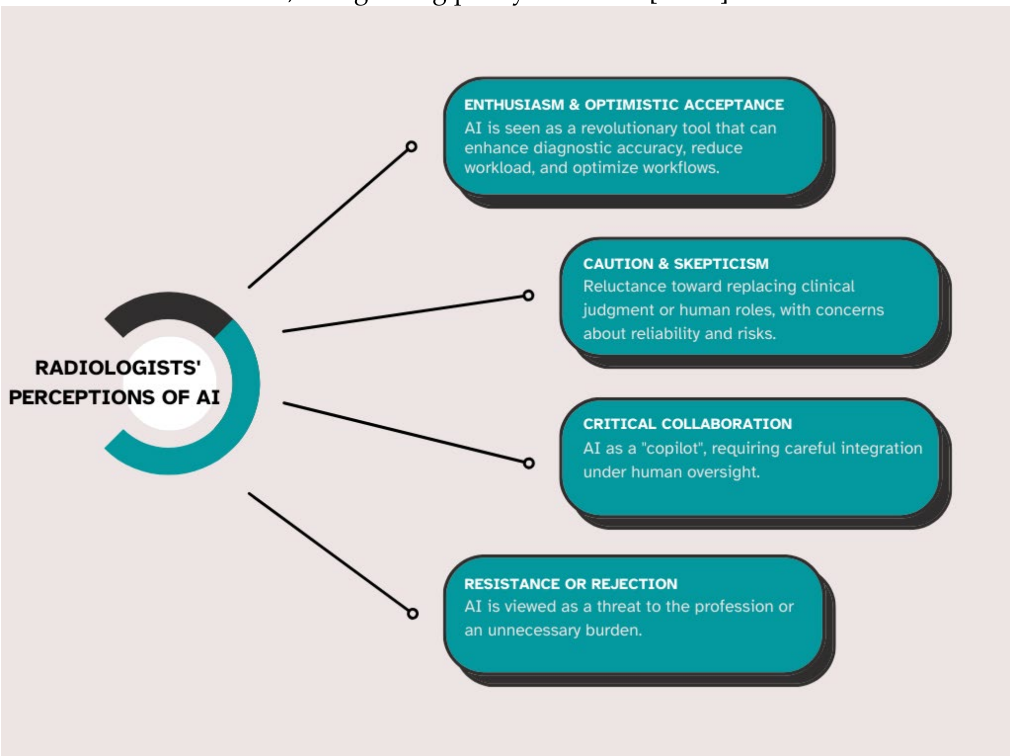

Figure 1. Illustration of the possible directions of perception of radiologists regarding the integration of artificial intelligence (AI) in the current radiological practice.

On the other hand, many studies evaluating radiologists' perspectives on AI predominantly employ qualitative methods such as interviews. However, few validated instruments exist to rigorously assess multidimensional constructs—including trust, workflow integration, and ethical considerations [25, 26]. The absence of standardized measurement tools hinders cross-study comparisons and limits the generalizability of findings.

The present study aims to validate the Radiologist Doctors’ Perceptions of Artificial Intelligence Questionnaire (RDPAIQ), a novel instrument designed to evaluate attitudes toward AI implementation in radiological practice. This research addresses the critical shortage of culturally adapted tools necessary to assess local barriers, professional readiness, and ethical concerns within specific healthcare contexts. Given that AI integration is no longer a theoretical prospect but a clinical imperative, understanding the perspectives of healthcare professionals is essential for ensuring its responsible and effective adoption. In the specific context of Romania—where hospital infrastructure development has lagged behind proposed modernization projects—evidence of technological awareness among physicians serves as a vital signal for public health authorities. Ultimately, this study underscores the need for systemic support to align current medical practice with rapid technological advancements.

2. Materials and Methods

In order to ensure internal validity and items reliability, the RDPAIQ underwent a rigorous validation process. As will be described below, after the initial questionnaire was designed, it went through several rounds of validation and a pre-testing phase on a restricted group of medical imaging experts. Thus, we have gone through these phases to assure that the instrument serves the objectives. Also, any ambiguous or confusing terminology was revised. Subsequently, we applied the questionnaire for the main study to a larger sample.

2.1. Study Design

The study adopted a quantitative approach, using a cross-sectional design to examine the perceptions of radiologists at a specific point in time. The main method of data collection was a self-administered questionnaire using Google Forms, allowing participants to express their opinions independently. The recruitment process was conducted via professional email.

The questionnaire remained accessible for completion between April 2025 and May 2025. This time frame was selected to allow sufficient opportunity for participants across various institutions and work schedules to respond, thereby maximizing response rates and ensuring a diverse representation of radiologists from both public and private healthcare settings from our university center in Iasi, Romania.

The main objective of the research was to thoroughly assess radiologists' perceptions of the implementation of AI in their daily professional practice. Therefore, this methodology was chosen to obtain an overview of the current attitudes and experiences of medical imaging specialists towards the integration of AI in the field of radiology.

2.2. Questionnaire Development and Structure

The RDPAIQ was designed with closed-ended items, i.e., predefined answers such as “Yes/No/Not sure,”, multiple choice, and Likert scale items. The questions were formulated in a clear, concise manner, without ambiguities. Double questions, which ask two things at once, were avoided. We also adapted the language to the target participants.

In its final form, the instrument consisted of a 24-item questionnaire. To increase the accuracy and validity of the measurement, the survey was structured into five sections:

(1) Demographics factors: This subscale was integrated with the role of collecting essential information about study participants, such as age, gender, or education level. For this section, we created four items.

(2) Experience with technology and AI: This subscale was designed with the aim of analyzing a subject's level of familiarity with AI, as previous experience with technology and AI can influence a person's perception, attitude, and comfort level regarding future advances in these areas. For this subscale, we formed two items.

(3) Perception of AI-assisted radiological diagnosis: This section was dedicated to analyzing how the subjects participating in the study perceive and understand the contribution of AI in the diagnostic imaging process. For this subscale, we created four items.

(4) Radiologist-AI interaction: This subscale assesses radiologists' views on the anticipation of physician-AI collaboration and how they understand this collaboration between radiologists and AI systems in medical practice. We developed nine items for this subscale.

(5) Challenges, ethics, and confidentiality in AI integration into radiological practice: The last section was designed to explore radiologists' perceptions and concerns regarding the integration of AI in diagnostic imaging. We developed five items for this subscale.

The RDPAIQ is available in the Supplementary Materials section.

2.3. Participant Demographics

The target population for this questionnaire was diagnostic radiologists that work in a public or private radiology department.

To ensure the relevance and specificity of the sample, rigorous inclusion and exclusion criteria were established. The inclusion criteria focused exclusively on active, practicing radiologists. Importantly, the study encompassed radiologists across all levels of training and professional development—residents, specialists, and primary care radiologists—allowing for a comprehensive analysis of perspectives and experiences across the full spectrum of clinical practice. This inclusivity strengthens the generalizability of the findings and offers valuable insight into how artificial intelligence is perceived and potentially integrated at various stages of professional formation.

Furthermore, participation was contingent upon each individual providing informed consent and expressing their willingness to complete the questionnaire in its entirety. Consequently, both physicians from specialties other than radiology and those who had retired or were no longer active in the field were not included in the study.

2.4. Content and Face Validity

Content validation was a critical step in the RDPAIQ development, as it ensures that it accurately measures the concepts it is intended to assess and that it is relevant and comprehensive for the target population. Therefore, content validation involved the assessment of the relevance, clarity, and comprehensiveness of the questionnaire items by experts in the field and practicing radiologists. This rigorous approach helped to establish the validity and reliability of the questionnaire, ensuring that it provides valuable data for a comprehensive analysis. Five senior radiologists and a head of clinic were enrolled in this process.

We also included a face validation to test how the questions are perceived, whether the format is understood correctly both lexically and conceptually. Four resident radiologists and two senior radiologists were enrolled in the face validation.

After these phases, the items were revised based on feedback received from experts consensus and enrolled participants.

2.5. Pre-testing Phase

To assess the effectiveness of our tool and to analyze the RDPAIQ format and its perception after the validation rounds, we conducted a pretest on a group of 10 radiologists similar to those in the sample. Following this pre-testing, we concluded that two questions were not relevantly formulated for the instrument, so we decided to modify them and ensure better relevance.

2.6. Testing Phase

We employed non-probability sampling to select the participants for the main testing, and the questionnaires were administered individually after signing the informed consent form. The responses were recorded in an anonymous way by using Google Forms. The estimated completion timeframe was approximately five minutes. A total of 74 diagnostic imaging doctors from the university center in Iasi, Romania, participated in the proper study.

2.7. Statistical Analysis

The statistical analysis was performed using Python version 3.13.2. This programming environment facilitates the implementation of advanced and customized statistical methods. Libraries such as NumPy, SciPy, pandas, and statsmodels provide powerful tools for data manipulation, the calculation of descriptive statistics, the performance of hypothesis tests, and the construction of complex statistical models.

2.8. Ethical Considerations

The research protocol for this study received official approval from the Ethics Committee of the University of Medicine and Pharmacy 'Grigore T. Popa' Iași (approval no. 421, date: 31.03.2024). This ethical oversight ensures that the study design adheres to the highest standards of integrity and participant welfare. All individuals who agreed to participate provided their written informed consent prior to data collection.

This process was conducted in strict accordance with the principles outlined in the Declaration of Helsinki [27]. Participants were explicitly informed about the voluntary nature of their involvement and were assured of their right to withdraw from the study at any time, without any negative consequences. These measures collectively ensured the protection of participants' rights and confidentiality throughout the research process.

3. Results

The RDPAIQ provides a structured framework for assessing attitudes, concerns, and perceived benefits, thereby offering critical insights for effective AI deployment strategies. Overall, the 24-item RDPAIQ was developed as a specialized instrument to systematically evaluate the multifaceted perspectives of radiologists regarding AI's role in diagnostics, workflow optimization, and professional development. Such insights are crucial for understanding the human factors influencing AI adoption and for designing effective strategies to mitigate potential resistance or optimize integration pathways.

3.1. Demographic profile of study participants

The sample studied included 74 radiologists, providing a basis for understanding their AI perceptions. In terms of gender, 27 participants were male (approximately 36.5%), while 47 participants were female (approximately 63.5%).

The average age of participants was approximately 33.3 years, with a standard deviation of 7.5 years, ranging from 25 to 61 years (see Figure 2). This suggests that the sample is relatively young, with a concentration around the age of 30, but also includes radiologists with more extensive experience (see Table 1).

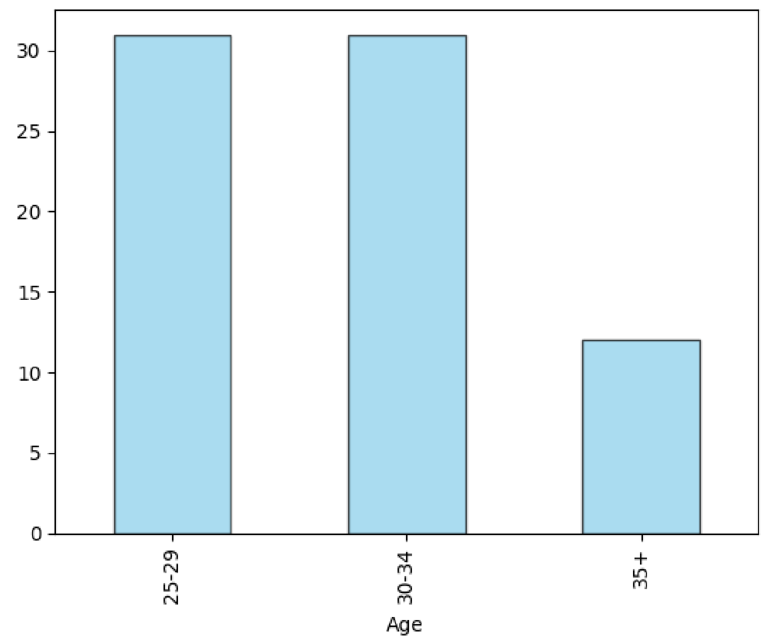

Figure 2. Histogram showing age distribution in the study group (N=74).

Demographic characteristic	Category/Value	N	% (Percentage)	Descriptive Statistics
Gender	Male	27	36.5%	N/A
	Female	47	63.5%	N/A
Age (years)	N/A	74	100%	Mean: 33.3 SD: 7.5 Range: 25–61
Radiology experience (years)	< 5 years	61	82.4%	N/A
	5 – 10 years	10	13.5%	N/A
	> 10 years	3	4.1%	N/A

Table 1. Demographic profile of study participants (N=74).

3.2. Validation of the Questionnaire

The Correlation Matrix indicator was calculated with the main purpose of highlighting correlations between the five sections of the questionnaire, but also between the items (see Table 2 and Figure 3).

Correlation Matrix					
Section	(1) Demographics factors	(2) Experience with technology and AI	(3) Perception of AI-assisted radio-logical diagnosis	(4) Radiologist-AI interaction	(5) Challenges, ethics, and confidentiality in AI integration into radiological practice
(1) Demographics factors	1.000	0.313	0.080	-0.034	0.032
(2) Experience with technology and AI	0.313	1.000	0.188	-0.023	0.169
(3) Perception of AI-assisted radiological diagnosis	0.080	0.188	1.000	0.257	0.484
(4) Radiologist-AI interaction	-0.034	-0.023	0.257	1.000	0.340
(5) Challenges, ethics, and confidentiality in AI integration into radiological practice	0.032	0.169	0.484	0.340	1.000

Table 2. Results of the "Correlation Matrix" analysis of the five sections.

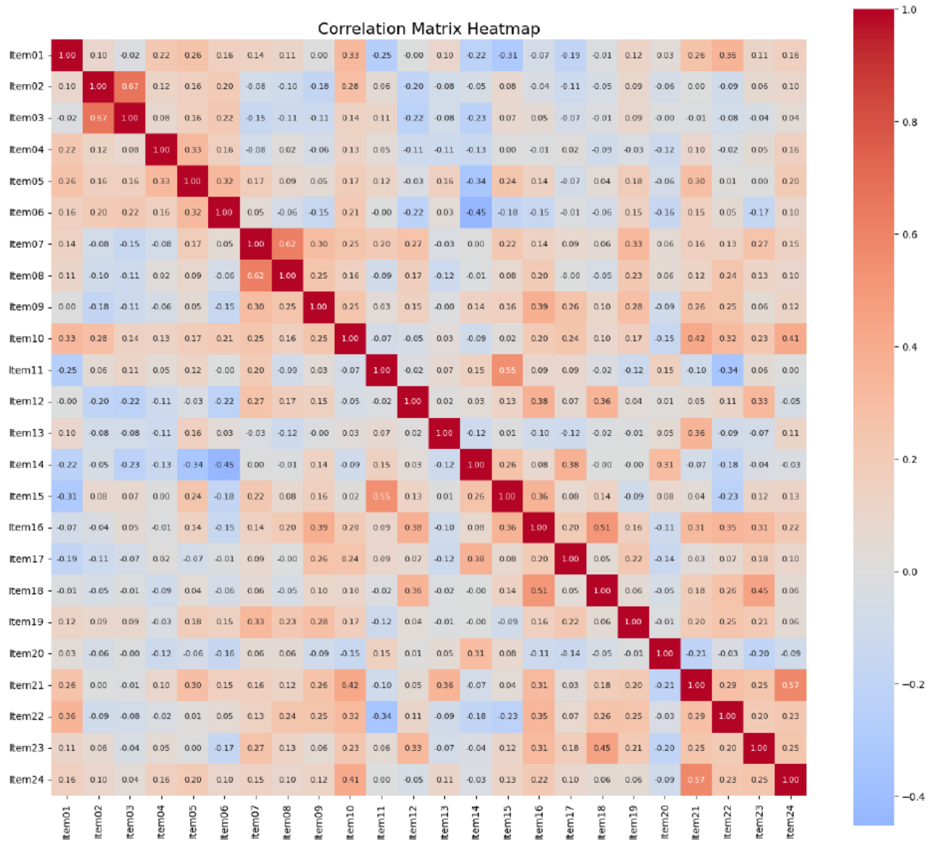

Figure 3. Results of the "Correlation matrix" analysis of the items of the questionnaire.

The analysis revealed a number of interesting correlations. For example, the correlation between the sections "(4) Radiologist-AI interaction" and "(5) Challenges, ethics, and confidentiality in AI integration into radiological practice" indicates a value of r=0.340. Similarly, the correlation between the sections "(3) Perception of AI-assisted radiological diagnosis" and "(5) Challenges, ethics, and confidentiality in AI integration into radiological practice" indicates a value of r=0.484.

While the global scale showed an Cronbach's alpha of 0.718, the multidimensional nature of the instrument necessitated subscale analysis. The reliability coefficients for the identified factors were as follows:

- (1) Demographics factors: 0.730;
- (2) Experience with technology and AI: 0.605;
- (3) Perception of AI-assisted radiological diagnosis: 0.708;
- (4) Radiologist-AI interaction: 0.702;
- (5) Challenges, ethics, and confidentiality in AI integration into radiological practice: 0.860.

Prior to conducting factor analysis, the dataset's suitability was evaluated using standard statistical tests. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy produced a value of 0.602. According to established guidelines, this value is considered acceptable, indicating that the sample is sensitive and adequate for a meaningful factor analysis.

Furthermore, Bartlett's test of sphericity was performed to confirm that the correlation matrix was not an identity matrix. The test yielded a Chi-Square value of 39.6718, which was statistically significant ($p<0.001$), with 10 degrees of freedom. This significant result confirms that the variables are sufficiently correlated to justify the application of factor analysis, demonstrating that the data do not originate from a population where all variables are uncorrelated.

Therefore, based on the factor analysis, the RDPAIQ items are grouped into several factors, and a principal component analysis is a good way to better understand the data structure and validate the constructs measured by the questionnaire. In the Scree Plot graph (Figure 4), the curve shows a rapid decrease in explained variance after the first component, followed by a smoother slope. This suggests that the first component is dominant. The fact that there are several relevant components indicates a multidimensional structure of the questionnaire, not a unidimensional one. In other words, the RDPAIQ does not measure a single concept. This aspect confirms the structural validity of the construct.

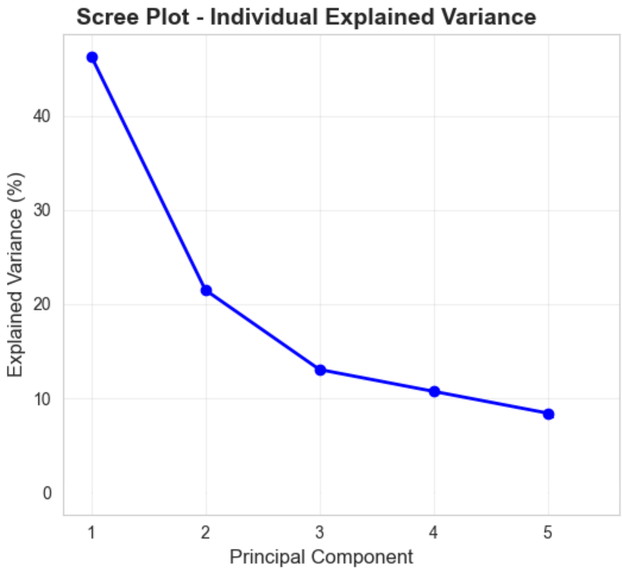

Figure 4. Scree Plot for factor extraction.

At last, we continued the analysis with the commonalities to see how well each subscale is explained by the extracted factors (see Table 3).

Commonalities					
Section	**(1) Demographics factors**	**(2) Experience with technology and AI**	**(3) Perception of AI-assisted radio-logical diagnosis**	**(4) Radiologist-AI interaction**	**(5) Challenges, ethics, and confidentiality in AI integration into radiological practice**
Communality	1.28	1.41	1.77	1.64	2.01
Percentage (%)	11.74	12.90	16.23	15.01	18.38

Table 3. Results of the commonalities analysis.

Thus, the subscale "(5) Challenges, ethics, and confidentiality in AI integration into radiological practice" has the highest communality (18.38%), which means that its variance is best explained by the identified factors. Also, the "(1) Demographics factors " subscale has the lowest communality (11.74%). This is expected and even desirable, as demographic data are not items of the theoretical construct, but context variables. The communalities confirm that the model is most appropriate for subscales related to the theoretical content of the questionnaire, rather than demographic ones.

4. Discussion

Nowadays, integrating AI into radiology practice is essential, considering the increasing demand for diagnostic imaging and the lack of qualified radiologists [28]. This process started with use of AI in medical settings, which has moved beyond the development stage and is currently being tested in many imaging centers and clinics [29]. Therefore, for AI to be properly integrated into the workflow, collaboration and adequate awareness of AI systems among radiologists is required.

Despite the positive potential of AI in diagnostic imaging, studies have reported that the inclusion of AI in radiology practice has led to increased rates of burnout among radiologists. For exemple, in a cross-sectional analysis of 6,726 radiologists, the adoption of AI was positively correlated with increased burnout prevalence, with evidence of a significant dose-response association [30]. However, in our study, questioned about how they believe the introduction of AI in radiology will influence the level of stress and pressure on radiologists (Item 18), 41.9% of respondents answered that it will decrease, while 36.5% said that AI will have no impact in this regard. Thus, the different results regarding burnout can be explained by the socio-cultural context in which the questionnaire was applied.

Thus, AI is revolutionizing the traditional approaches in medical imaging, and this transition and innovation is currently underway. DL algorithms demonstrate their capabilities in identifying patterns and anomalies in large sets of imaging data, enabling their application in many areas of diagnostic imaging, such as nodule detection, fracture classification, and tumor volume quantification with remarkable accuracy. In this regard, with the paradigm shift in radiological diagnosis, current studies should also focus on the level of training of radiologists in AI, but especially their perceptions and expectations regarding the new technologies they are expected to work with [26, 31-33].

Medical imaging and radiology, as a data-driven specialty, is at the forefront of integrating AI tools into healthcare practice, and radiologists are undoubtedly among those doctors whose workflows will be most affected by AI. Certainly, there are many barriers preventing the widespread adoption of AI, primarily resistance from radiologists [34]. However, several experts in AI posit that the future role of physicians will increasingly involve a collaborative paradigm, integrating human medical expertise with machine-driven decision-making [35].

In our research, we developed the RDPAIQ consisting of five subscales with the aim of understanding radiologists' insights on integrating AI into diagnostic imaging. Thus, the "(1) Demographics factors" subscale of our questionnaire aimed to collect essential demographic data about the study participants, including age, gender, and education level. These informations are crucial for a contextual analysis, as it allows for the examination of how factors such as professional experience or age influence attitudes and perceptions toward AI. Demographic data also facilitates the grouping of respondents and the identification of potential correlations between individual characteristics and expressed opinions. For example, in our study, based on the one-way ANOVA test, the question regarding the subjects' experience in radiology (Item 3) and the question regarding the reduction in time spent by radiologists interpreting radiological images using AI (Item 12) were correlated, and this correlation was statistically significant ($p = 0.0057$). This shows that younger physicians, particularly those with less experience, recognize the growing importance of AI in medicine. Overall, radiologists are concerned about the increasing volume of indispensable imaging studies essential for modern medical diagnosis, which in turn leads to less time allocated for each individual examination. Consequently, younger physicians believe that AI will be a valuable tool to help them manage this workload more effectively.

Furthermore, we also included the "(2) Experience with technology and AI" subscale in our questionnaire, designed to measure the subjects' level of familiarity with

AI systems. The rationale behind this subscale is that prior experience with technology, especially with AI-based tools, can significantly influence a medical professional's perception, attitude, and comfort level regarding the future adoption of these technologies in radiology. By evaluating this subscale, we can distinguish between attitudes based on familiarity and those stemming from a lack of exposure. In our survey, regarding their familiarity with the concept of AI in radiology (Item 5), 8.1% of the respondents reported being very familiar. The distribution of responses further revealed that 32.4% indicated they were quite familiar, and a plurality of 48.6% reported a moderate level of familiarity. A smaller proportion, 9.5%, stated they were slightly familiar, while 1.4% indicated they were not very familiar with the concept. These results are promising, as a solid baseline of moderate familiarity is a critical starting point for successful AI adoption. However, they also suggest a need for further education and training to transition from passive awareness to active engagement. The moderate familiarity level might reflect a general understanding of AI's potential and applications, but it doesn't necessarily imply proficiency in using AI tools or a deep grasp of their underlying principles and limitations.

In addition, the "(3) Perception of AI-assisted radiological diagnosis" section was dedicated to analyzing the participants' perception and understanding of AI's contribution to the diagnostic imaging process. The RDPAIQ explored aspects such as the perceived accuracy of AI systems, their usefulness in detecting anomalies, and the trust that radiologists place in these systems. Measuring this subscale is fundamental to understanding whether radiologists view AI as a reliable and complementary tool capable of optimizing workflow and improving diagnostic precision.

Moreover, the subscale on "(4) Radiologist-AI interaction" assessed participants' views on the collaboration between clinicians and AI systems. It analyzed how radiologists anticipate this collaboration, including the role they will play in tandem with AI. The questions addressed aspects such as the allocation of responsibilities, communication with AI, and the harmonious integration of AI systems into the daily workflow, aiming to identify perceptions of the future dynamic of the doctor-technology team. In this regard, a substantial majority of the study participants, specifically 70.3%, believe that the integration of AI will not fundamentally alter the radiologist's role in the diagnostic process, but will instead serve as a complementary tool. The findings suggest that the integration of AI is not perceived as a disruptive force but as an evolutionary step that will transform the radiologist's role for the better, making it more focused and efficient. This perspective is a crucial factor for the smooth and ethical implementation of AI technologies in healthcare.

The last subscale – "(5) Challenges, ethics, and confidentiality in AI integration into radiological practice" – was designed to explore radiologists' perceptions and concerns regarding the integration of AI into imaging practice. It investigated critical aspects such as practical challenges (e.g., integration into existing infrastructure, the learning curve), ethics (e.g., who bears final responsibility in case of error), and data confidentiality (e.g., security risks). Analyzing these aspects is vital for anticipating and proactively addressing the obstacles and ethical dilemmas that may arise with the large-scale implementation of AI in the medical field.

Ultimately, according to the statistical analysis, the RDPAIQ is valid and reliable, with good internal consistency. Also, our questionnaire is multidimensional, measuring not a single concept but a series of interrelated concepts. Furthermore, the communalities confirm that the model is most appropriate for the subscales related to the theoretical content of the questionnaire, rather than for the demographic ones.

Our research presents some limitations that need to be mentioned. To begin with, this is an unicentric study and includes a small number of participants. The demographic profile of the sample suggests a significant skew toward early-career professionals, with a mean age of 33.3 years and a vast majority of participants (82.4%) having less than five years of clinical experience. While this reflects the high engagement of 'digital natives' with emerging technologies, it limits the generalizability of our findings to the broader radiology community. Senior radiologists, who may possess different clinical priorities or higher levels of skepticism regarding AI integration, are underrepresented in this cohort. Consequently, the attitudes captured here may more accurately reflect the perspectives of residents and junior consultants rather than the entire professional spectrum. Furthermore, the results are preliminary, and the limited sample size restricts the statistical power and external validity. Also, the KMO measure of sampling adequacy was 0.602. According to standard psychometric benchmarks, this value is considered 'mediocre' or barely acceptable for factor analysis. This result is likely a reflection of the modest sample size and the inherent heterogeneity of the initial item pool. While the Bartlett's Test of Sphericity confirmed that the data were suitable for factor extraction ($p < 0.001$), the KMO value suggests that future iterations of the RDPAIQ should be tested on a larger, more diverse population to achieve a more robust factorial structure and improve sampling adequacy indices.

Nonetheless, the findings suggest that this sort of questionnaire opens up a promising perspective and emphasize the need of putting it into practice. By identifying specific knowledge gaps and attitudinal barriers, hospitals can transition from generic IT training toward targeted educational interventions that address the unique concerns of different professional cohorts, such as the perceived loss of autonomy or technical literacy. In healthcare environments where physical infrastructure has historically lagged behind technological potential, the empirical data provided by the RDPAIQ offers a rigorous evidence base for hospital boards to lobby public health authorities for necessary systemic investments. Ultimately, the questionnaire provides a foundational framework for developing local ethical protocols and liability guidelines, ensuring that the integration of AI into clinical workflows is not only technologically advanced but also professionally accepted and ethically responsible.

Thus, we intend to expand this research with a larger sample size and welcome colleagues from other national and international centers to participate in this scientific endeavor. Moreover, the majority of the study's respondents were young radiologists. This raises several discussion hypotheses, such as the fact that older practitioners may be more reluctant when it comes to implementing AI in healthcare.

5. Conclusions

In conclusion, the impact of AI in diagnostic imaging extends beyond workflow optimization, enabling the early identification of subtle anomalies that might go unnoticed by the human eye. This capability contributes to earlier disease detection and the initiation of personalized treatment plans. Therefore, understanding how radiologists perceive the impact of AI is essential.

Our study developed and validated a questionnaire to assess radiologists' perceptions of AI integration in diagnostic imaging. The RDPAIQ demonstrated acceptable reliability and suitability for factor analysis, confirming its utility for clinical AI readiness assessment. Understanding these perceptions is vital for mitigating potential biases and ethical concerns associated with AI deployment, thereby ensuring an equitable and responsible clinical application.

The RDPAIQ can be applied in radiology clinics and departments to identify potential barriers, anticipate training needs, and align implementation strategies with the practical realities of the profession. Without a thorough understanding of radiologists' perceptions, any attempt to integrate AI risks encountering resistance, generating operational inefficiencies, and compromising the anticipated benefits. Furthermore, a systematic analysis of these perceptions allows for the development of regulatory frameworks and health policies that support a fair and efficient transition to AI-augmented radiology.

Supplementary Materials: The following supporting information can be downloaded at: www.mdpi.com/xxx/s1, Figure S1: title; Table S1: title; Video S1: title.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

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Conflicts of Interest: The authors declare no conflicts of interest.

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