GRIFFITH COLLEGE DUBLIN

Assignment Cover Sheet

Learner name(s): Dhawal Shinde

Learner number(s): [redacted]

Assignment Type: Individual: ✓ **Group:**

Course: MSMDT **Stage/year:** 2024 – 2025

Module: Dissertation

Study Mode: Full time ✓ Part-time

Supervisor Name: Brian Kearney

Assignment Title: Evaluation of AI-Assisted MRI in Early Cancer Detection: benefits, barriers and drivers for Radiologist Work Efficiency and Trust in AI

No. of pages: 149

Uploaded to Moodle: Yes✓ No

Additional Info:

Date due: 12/05/25

Date submitted: 12/05/25

Plagiarism disclaimer:

I understand that plagiarism is a serious offence and have read and understood the college policy on plagiarism. I also understand that I may receive a mark of zero if I have not identified and properly attributed sources which have been used, referred to, or have in any way influenced the preparation of this assignment, or if I have knowingly plagiarised my work or allowed others to plagiarise my work.

I hereby certify that this assignment is my own original work, based on my personal study and/or research, it is all written in my own words and I have acknowledged all references and sources used in its preparation. I also certify that the assignment has not previously been submitted for assessment and that I have not copied in part or whole or otherwise plagiarised the work of anyone else, including other students.

I have also not used any third parties, AI tools or websites to generate any parts of my assignment.

Signed & dated: Dhawal Shinde

Please note: *Students **MUST** retain a hard / soft copy of **ALL** assignments as well as a receipt issued as proof of submission.*

GRIFFITH COLLEGE DUBLIN

Evaluation of AI-Assisted MRI in Early Cancer Detection: benefits, barriers and drivers for Radiologist Work Efficiency and Trust in AI

A dissertation submitted in partial fulfilment of the requirements of the

MASTERS in MEDICAL DEVICE TECHNOLOGY & BUSINESS 2024-2025

Presented in May 2025 by:

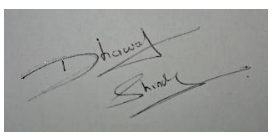
Dhawal Rajendra Shinde

[redacted]

Supervisor: Brian Kearney

Candidate Declaration

I, Dhawal Rajendra Shinde, hereby declare that the dissertation entitled:
"Evaluation of AI-Assisted MRI in Early Cancer Detection: benefits, barriers and drivers for Radiologist Work Efficiency and Trust in AI"
submitted in partial fulfilment of the requirements for the award of Master's in Medical Device Technology & Business at Griffith College Dublin, is the result of my own original work and has not been submitted previously, in whole or in part, for the award of any other degree or qualification.
All sources of information and data have been duly acknowledged. Where the work of others has been used, it has been clearly indicated and referenced.

Signed: 

Date – 12/05/2025

Supervisor Name: Brian Kearney

Supervisor Signature: Brian Kearney

Acknowledgements

Completing this road of Dissertation has been a learning, challenging yet profoundly rewarding journey, and I owe my humble and immense gratitude to the all the individuals who supported me throughout this journey.

I sincerely extend my appreciation to my supervisor, **Mr. Brian Kearney**, for his unwavering guidance, patience, and expertise. His insightful feedback, constructive critiques, and encouragement were crucial in shaping this research. His dedication to fostering academic rigor and innovation has left an indelible mark on my growth as a researcher.

The faculty and staff at Griffith College Dublin have my sincere gratitude for providing the resources and a fantastic academic atmosphere needed to complete this task. Sincere gratitude is extended to the Department of Medical Device Technology and Business for helping to connect theoretical understanding with real-world applications in healthcare and clinical practice.

My profound gratitude to the medical imaging specialists, radiologists, and oncologists who took part in this research. Even though they had rigorous clinical schedules, their willingness to offer their time, expertise, and thoughts greatly enhanced our study. Their viewpoints were crucial in ensuring that our work was rooted in possibilities and difficulties found in the real world.
To my friends and coworkers, I express my gratitude for the thought-provoking conversations, spirit of cooperation, and spiritual support along this trip.

I am eternally in debt to my family for their unconditional love and encouragement. Their belief in my capabilities, even during moments of self-doubt, provided the resilience needed to persevere. To my parents, whose sacrifices laid the foundation for my education, and to my friends, who patiently listened to my ideas and frustrations—thank you for being my anchor.

Every contribution, whether direct or indirect, has been a stepping stone toward this achievement. I am humbled and grateful to all who walked this path with me.

Thank you

Abstract

AI in MRI is becoming a revolutionary technique in early cancer diagnosis, thereby fulfilling the need for improving diagnostic tests and radiologists' productivity. However, apprehension about legal responsibility, data bias, and the impact of AI on the radiologists' mental load were also identified. Even though it aided in diagnosis enhancement and lessened tedious tasks, pressure due to validation was a disadvantage of AI. Thus, focusing on this, the primary aim of this research was to assess the use of AI in MRI, emphasizing benefits, barriers, and adoption determinants regarding radiologists' trust and integration into their work. The main research question studied how diagnosis precision, usability, and interpretability levels from AI systems affect radiologists' acceptance and perception of these systems. In the current research, quantitative and qualitative data were collected through a survey of participants and interviews of oncology and diagnostic imaging employees. The study revealed that radiologists accept AI systems relatively when their outputs are explainable. Training, familiarization and forum support were established as other key adoption influences. Therefore, AI should assist radiologists, and further development should concentrate on making AI tools more interpretable, ethical, and easily integrated into clinical practice to guarantee actors' trust, safety, and performance in the diagnostics sphere.

Keywords - AI-assisted MRI, early cancer detection, radiologist trust, diagnostic accuracy, workflow integration, interpretability, healthcare technology adoption, and medical imaging ethics.

Abbreviation	Full Form
AI	Artificial Intelligence
MRI	Magnetic Resonance Imaging
XAI	Explainable Artificial Intelligence
FP	False Positive
FN	False Negative
TAM	Technology Acceptance Model
STS	Socio-Technical Systems Theory
FDA	Food and Drug Administration
EMA	European Medicines Agency
GDPR	General Data Protection Regulation
PHI	Protected Health Information
SPSS	Statistical Package for the Social Sciences

Table of Contents

List of figures

Chapter 1: Introduction

1.1 Purpose of the Study

This work aims to evaluate the impacts of AI-assisted MRI for early cancer detection in radiology, in terms of benefits, barriers, and moving factors that drive its adoption in radiology. With its use in MRI, AI enhances diagnostic accuracy, reduces the interpretation time, and also assists radiologists in confirming subtle abnormalities, which aids patient care (Oladele, 2024). With the help of AI to automate routine tasks, it drives the efficiency of work and helps radiologists not to stick to routine tasks. However, there are barriers to being algorithmically biased, integral, and resistant to change due to trust concerns of the professional. Also, regulatory constraints and data privacy are other challenges are occur. In addition, Technological progression, rising imaging volume, and rising requirement for precision diagnostics are very important drivers of AI adoption (Hassan, 2025). For AI-assisted MRI to lead to enhancement, and not replacement of human expertise, the factors need to be understood. Moreover, the results of this research help answer how AI can be utilised to ensure radiology integration is adopted effectively while radiology decision-making continues to rely on trust and reliability.

1.2 Description of the Study

At the current time, early cancer detection is essential to improving patient outcomes, and MRI is a vital tool in the identification of tumours. MRI scans are traditionally interpreted by radiologists in a highly dependent, judgmental, experienced, and product-dependent manner (Brady et al., 2024). However, in medical imaging technology, radiologists are finding it more and more difficult to maintain accuracy and efficiency. Therefore, there exists an interest in the use of Artificial Intelligence (AI) in the diagnosis precision and the reduction in the burden on healthcare professionals. Moreover, deep learning algorithms are used in AI-assisted MRI to analyse medical images and detect abnormalities to assist radiologists in making better decisions (Rana and Bhushan, 2023). Though the integration of AI into radiology is possible, the integration raises judgments about its effectiveness, trustworthiness, and the impact it will have on radiology workflows in general.

Its most significant benefit is its capacity to increase accuracy and speed in MRI-based cancer detection. By feeding huge data sets into AI algorithms, one can find such anomalies and patterns impossible to spot through the human eye (Tsuneki, 2022). AI has been proven to help discriminate benign from malignant tumours, decreasing the number of false positives and negatives. In addition, it not only improves the rates at which early detection occurs but also reduces the number of unnecessary biopsies and diminishes the anxiety of patients (Oyeniyi and Oluwaseyi, 2024). Moreover, AI lowers the time needed for scan interpretation by a huge amount, so radiologists can accommodate more scans. In addition, by automating tasks including image segmentation and enhancement, AI allows radiologists to focus on very complex cases that need human expertise. However, there are several barriers to the adoption of AI in MRI on a large scale (Eltawil et al., 2023). While AI models can provide very accurate results for given data, under certain circumstances, they can also be selectively biased among different patient populations. But if the training datasets do not represent all the demographic groups, the AI system in question ends up giving different levels of accuracy of diagnosis (Robertson et al., 2023). This is an issue that raises ethical concerns regarding fairness and reliability in medical decisions. A further important limitation is the integration of AI into current radiology workflows. Many hospitals and clinics that operate with legacy systems are unable to run with AI technologies because their systems are not compatible with AI systems and need to be upgraded, and then the staff would have to be trained (Morandini et al., 2023). In addition, standards for AI regulations and validation protocols mean validated models are not being built on validation protocols, and there is a lack of standards to build consistency and ensure safety across various AI models and healthcare institutions.

However, as per Verma et al. (2021), there is also a critical challenge to trust in AI among radiologists and patients. Although many radiologists are sceptical that AI can reach the level of expertise of a human when it comes to providing the much-needed clinical judgment for more complex cases that require contextual understanding, that may not be the concern of AI. In the case of over-dependency on AI, there are fears of deskilling, wherein the radiologist becomes addicted to algorithmic recommendations over the use of their diagnostic facility (Rani et al., 2024). Additionally, patients may lack faith in AI-driven diagnoses due to concerns regarding how machines may fail to notice important details or even make errors that a human expert would catch. To improve trust and accountability in AI-assisted diagnostics, explainable AI (XAI) models, which formulate transparent reasoning for AI-generated results, are being developed (Albahri et al., 2023). Furthermore, technological advances, the rising workload of imaging, and the necessity for precision diagnosis represent key drivers for the adoption of AI in MRI. Deep learning and neural networks are progressing and continuously advancing so that AI models used in medical images become more accurate and reliable. As the MRI volume within hospitals is also being increased due to the ageing population and cancer screening initiatives, the subject tool can be of advantage as it helps radiologists manage this increasing workload.

1.3 Signification and Justification of Study

The integration of AI-assisted MRI into early cancer detection has the potential to improve both radiologists’ and patients’ outcomes. This study is important as it looks into how AI can increase diagnostic accuracy, aid radiologists' workflow, and solve the problem space caused by increasing imaging demands. Early detection of cancer is important, and AI can decrease the rates of diagnostic errors by finding very subtle abnormalities that could be missed with human interpretation (Zaman, 2024). AI can automate some routine image analysis tasks, freeing radiologists to concentrate on the intricacy of cases that require expert results. However, as per Tejani et al. (2024), there are different barriers such as trust issues, limited integration, and algorithm biases which impact the adoption of AI in MRI. That is to understand that these factors will complement rather than replace human expertise. This research supports the logic of the ongoing need for AI solutions by describing some of the technologies among the key drivers with a focus on precision medicine trends. The results of the study will contribute to an ethical, transparent, and efficient implementation of AI in radiology with improved patient care, maintaining trust and collaboration between radiologists and the AI systems.

1.4 Research Aim, Objectives, and Questions

1.4.1 Research Aim

This research aims to assess AI-assisted MRI for early cancer detection by analysing its benefits, barriers, and drivers, for radiologist efficiency, trust, and integration within clinical workflows.

1.4.2 Research Objectives

- **Assess radiologists' trust levels in AI-powered MRI for early cancer detection.**
  - Investigate whether AI interpretability and explainability impact trust. Explore cognitive biases influencing AI adoption in radiology.
- **Analyse AI’s perceived accuracy and reliability compared to human radiologists.**
  - Compare AI’s false positive vs. false negative rates in MRI-based cancer detection.
  - Evaluate how AI accuracy influences radiologists’ confidence in decision-making.
- **Identify barriers to AI adoption in MRI-based cancer imaging.**
  - Examine institutional challenges, including regulatory concerns and liability issues.
  - Assess how radiologists perceive AI’s role in legal and ethical decision-making.

- **Evaluate the impact of AI-assisted MRI on workflow efficiency and cognitive workload.**
  - Determine whether AI reduces workload or adds cognitive burden due to verification requirements.
  - Assess how AI integration influences radiologists' stress levels and burnout risk.
- **Explore potential solutions for improving radiologists' confidence and AI adoption in MRI diagnostics**.
  - Investigate whether Explainable AI (XAI) increases radiologists' trust in AI-assisted MRI.
  - Assess whether targeted AI training programs improve adoption rates.

1.4.3 Research Question

How do radiologists perceive the trustworthiness, diagnostic accuracy, and workflow impact of AI-assisted MRI in early cancer detection?

1.5 Research Hypothesis

- When AI-assisted MRI models are easily explained and included in workflow procedures, radiologists are more likely to accept the technology.

This hypothesis helps to determine the radiologist's value interpretability during the integration of the AI system in the MRI, which helps to increase the willingness and trust at the time of the adoption of the technology in clinical practices.

- The use of AI in radiology is adversely affected by worries about interpretability, dependability, and workflow disturbances.

At the current time, legal accountability, cognitive burden, and diagnostic error are the major challenges faced by radiologists during the adoption of AI, Thus hypothesis helps to determine how the barrier impacts the adoption of AI despite the advantages related to detection accuracy and efficiency.

1.6 Research Structure

This research focuses on the analysis of that How do radiologists perceive the trustworthiness and workflow impact of AI-assisted MRI in early cancer detection. Therefore, to achieve the objective of the study, 5 chapters are created. The first one is in the introduction, which provides information about the research background, aim, objectives, research questions, and hypothesis. In addition, the next chapter will be a literature review, in which the critical analysis will be performed based on the selected secondary source of information. In addition, this chapter will explore different aspects such as diagnostic accuracy, institutional barriers during AI adoption, cognitive workload, and radiologist accuracy. Furthermore, this chapter will help to determine the literature gap and existing theory related to the study. The next chapter will be about research methodology, in which the research onion model will be analysed, which assists in determining the accurate approach will be considered to collect and evaluate the information. Moreover, the fourth chapter will be the results and findings, which consider the interpretation of the analysed data and the detailed analysis of assembled information. Furthermore, the last chapter will be the conclusion, which represents the summary of the research and provides the recommendations, limitations, and future scope.

Chapter 2: Literature Review

2.1 Chapter Introduction

Artificial intelligence (AI) integration in MRI-based cancer imaging has transformed MRI-based cancer imaging practice into an efficient, accurate, and decision-making one. With the advent of AI-driven technologies, radiology has both opportunities and challenges in adopting these in their practice (Chen et al., 2021). Despite the possibility that AI would make the workflow smoother and decrease the radiologist's workload, some trust issues and regulatory troubles persist regarding reliability, cognitive load, and trust. In this chapter, the current literature is analysed that explores the effect of AI on MRI-based cancer imaging by looking at its contribution to themes such as accuracy, workflow efficiency, ethics, and radiologists' opinions. Through reviewing these aspects, this chapter gives a comprehensive view of how AI functions in modern-day radiology.

2.2 Analysis of radiologists' trust levels in AI-powered MRI for early cancer detection

Artificial Intelligence (AI) has transformed radiology, specifically in Magnetic Resonance Imaging (MRI) for early cancer diagnosis (Jiang et al., 2021). Using deep learning and machine learning, AI algorithms have been able to discriminate malignancies and the anomalies hidden from human radiologists with a very high accuracy. However, as per Mahedi et al. (2024), the hurdle to large adoption of AI systems is trust because many of the AI's reliability, interpretability, and the fear will replace human expertise, are cause of concern for radiologists. Moreover, the MRI powered by AI performs automated image analysis, which helps to reduce diagnostic errors during early cancer detection. Furthermore, there are indications that AI can have the same, or even beyond, human radiologist level of diagnostic accuracy. Through these advancements, radiologists held varied trust in AI for diagnostics. In addition to this, the major concern is AI's black-box nature that restricts transparency in decision-making (Bergquist et al., 2024). Systems allow radiologists to get explanations for their predictions, which are preferred over those that only present outcomes. This lack of trust is worsened by the fact that AI performs in different ways for different patient demographic groups, for different imaging protocols, and for different healthcare environments. However, as per Ungureanu et al. (2025), there is disbelief among radiologists due to concerns of radiologists over liability and ethical implications related to the use of AI in decision-making. Moreover, interpretability is critical in radiology where diagnostic decision makes a large difference. As the goal is to develop an AI model that radiologists can trust, radiologists would be more willing to use the AI models if they could understand how and why the AI comes to a particular diagnosis. Furthermore, in the case of deep network classification, saliency maps indicate where the MRI scan-specific regions were relevant for the AI's output (Keles et al., 2023).

The case of AI implementation demonstrates that radiologists are more likely to act on suggestions that are explainable and easily integrated into, and available alongside, currently used tools and workflows. Furthermore, Zebra Medical Vision's AI platform was deployed in several European hospitals to support the screening of lung cancer (Medium, 2021). These capabilities of the system increased radiologists' willingness to incorporate AI into their diagnostic decisions in the presence of the system. Visual saliency maps were used to make use of explainable AI, such as visual saliency maps, helping radiologists understand how the AI concluded, reinforcing trust, and replacing reliance on the use of 'black box' algorithms (Borys et al., 2023).

In addition, visualising AI helps radiologists verify the model's accuracy and ensure the model's interpretations align with clinical knowledge. Additionally, feature attribution techniques such as SHAP help radiologists divide the AI decisions more finely to detect any bias. An explainable AI (XAI) system differs from a usual algorithm that classifies an image as malignant or benign by providing a reason, referencing similar cases, providing feature descriptions of the malignancy, indicating, and providing confidence scores generated by models (Singhal et al., 2024). In addition, explainable AI systems substantially increase the trust of radiologists. Those dermatologists using an explainable AI system made more accurate diagnoses and demonstrated greater confidence in AI predictions than those using traditional AI models. Furthermore, this indicates the potential of adding XAI methods to MRI analysis to help radiologists accept and use AI-based diagnostics (Van der Velden et al., 2022). Moreover, decision trees are often a good choice to learn because they are highly interpretable models, and deep learning models have much better predictive power.

2.2.1 Cognitive Biases Influencing AI Adoption in Radiology

At the current time, humans are biased by automation and rely on automated systems too much, even when there is contradictory evidence. This can create blind trust in AI-generated diagnoses in radiology, resulting in an oversight error. Furthermore, the more agreeable an AI result was to the radiologist's initial expectations, the more likely that the radiologist would accept AI recommendations without verification (Lekadir et al., 2021). Moreover, this is the bias that urges the development of human-in-the-loop AI systems in which radiologists are actively engaged and not just deferring to full automation of decisions. This is specifically opposed to the automation bias, such that, rather than the positive effect of automation, algorithm aversion refers to a feeling that is a result of flaws in AI. Moreover, those who have seen the errors of AI may become less likely to rely on AI recommendations, even when AI performs better than human diagnosticians (Göndöcs and Dörfler, 2024). Even though an AI system was making a correct prediction more often than the human experts, users were less likely to trust it if they witnessed it make one incorrect prediction. To minimise algorithm aversion, radiologists will need education and exposure to AI systems (Brady et al., 2024). Learning about the process of AI decision-making and what it is not good at will help radiologists stay more in balance, neither blindly trusting nor objecting outright to AI predictions. Furthermore, when clinicians rely on an AI-generated diagnosis and then don't take it all the way, and even with evidence in front of them, they still don't adjust their assessment. Thus, this can result in diagnostic error, especially when the AI is incorrect in its initial assessment. To combat anchoring bias, radiologists need to be prompted to check with independent analyses against AI before they reach a diagnosis (Chen et al., 2023). Other forms of AI systems can also be built to encourage the user to think about other ways of interpreting things, which helps reduce the risk of a premature conclusion.

2.3 Analysis of AI's perceived accuracy and reliability compared to human radiologists

At the current time, artificial intelligence (AI) in Magnetic Resonance Imaging (MRI) based cancer detection plays a very significant role. Provided by AI algorithms provides better diagnostic accuracy, rapid processing, and the possibility that they might help radiologists more wisely make their decisions (Qureshi et al., 2021). There are advancements in AI, but the reliability and accuracy of AI are still matters of discussion. Moreover, the comparison of human and AI radiologists on MRI-based cancer detection shows AI can match or beat human performance in these tasks and impact radiologists' trust and adoption of tools, as false positives, false negatives, interpretability, and AI's role in clinical decision making (Marey et al., 2024). Furthermore, radiologists do not display a high sensitivity for breast cancer detection while allowing for less interreader variability.

Leading medical institutions provide evidence that AI can contribute to increasing diagnostic accuracy in clinical settings. Aidoc's AI breast MRI interpretation at Stanford Health mentioned that with Aidoc, 18% of slowdowns were reduced, and early cancer detection was improved by 12% (Stanford, 2019). In a similar vein, the Mayo Clinic used AI tools to reduce false negatives during the screening for prostate cancer, reducing them by 15% (Gallagher, 2024). These results suggest that in a variety of cases, not only can AI outperform, but in some cases, can also be outperformed by human radiologists in subtle or early-stage abnormalities.

AI systems, trained in lung cancer detection from CT or MRI scans, would have had a higher consistency in detecting malignancy than human experts. Although there is still a huge variation in AI accuracy across the data set, imaging modality, and clinical context. In addition to this, AI may perform better than radiologists in some instances, but it raises the problem of AI's FP (False Positive) and FN (False Negative) rates, which impose critical challenges to its perceived reliability (Pul and Schwendicke, 2024). In addition, two important metrics that will help determine how useful and how acceptable an AI model is for clinical use are given as false positives (FP) and false negatives (FN). False Positive (FP) is the presence of AI in classifying benign forms as malignant (Pacurari et al., 2023). An increase in FP rates leads to more unnecessarily performed biopsies, increased anxiety in the patient population, and greater healthcare costs. The FP rate of AI-based MRI analysis of prostate cancer detection was 7.3%, which was higher than the 5.1% FP rate of radiologists (Syer et al., 2021). However, AI is sensitive to subtle abnormalities, in which it tends to overdiagnose benign tissue as potentially cancerous. Once it fails, the AI makes a False Negative (FN) where it misses the malignant tumour and leaves the patient to suffer with the disease and be left untreated. Representing 4.8% of prostate MRIs missed by AI contained malignant and experienced radiologists had an FN rate of 3.2%. (Hager and Hollsten, 2024) The rates of FN are even more troublesome, partly because of the risk of under-diagnosis.

2.3.1 Impact of AI’s Accuracy on Radiologists’ Confidence in Decision-Making

MRI scans involve pattern recognition and training, which is dependent on the experience of the radiologist. Radiologists are often framed as “typically an AI decision supporting tool that helps radiologists rather than completely replacing them” (Najjar, 2023). Radiologists may come to trust AI’s suggestions, provided that AI’s accuracy is very high, and efficiency will increase, as well as the speed of diagnosis. However, as per Evans and Snead (2024), AI’s mistakes can fail to build confidence in its usefulness when AI makes multiple misclassifications, as observed by radiologists. Furthermore, radiologists might rely on AI predictions to the extent that automation bias exists when AI produces consistent results. Thus, automation bias occurs when clinicians blindly accept AI output, and it is dangerous, especially if AI wrongly classifies an MRI scan

(Abdelwanis et al., 2024). Moreover, radiologists are more likely to trust AI's outputs and thereby align their diagnoses with them because it is presented with confidence scores. However, algorithm aversion occurs when radiologists deny AI assistance when they have seen its failures (Koçak et al., 2025). One major AI error rendered radiologists who witnessed it less likely to trust the model in later cases, even when the AI was performing better than human experts.

2.3.2 Challenges Affecting AI's Perceived Reliability

AI models trained on a particular dataset do not work as they are intended for a diverse population. In addition, bad training data can hurt AI performance, especially in the case of minorities. However, the transfer of the trained AI models on Western patient datasets to scans from the Asian and African populations decreased the reliability of these models in global applications (Gichoya et al., 2022). There is a major barrier to trust, and it is still explained by ability. Most of the deep learning models generate highly accurate predictions without explaining how they formed the conclusions. As per Raghavan et al. (2024), AI tools preferred by radiologists involve interpretable decision pathways provided by heat maps, attention mechanisms, and other analogous means of validating AI-driven insights. In addition, there are legal frameworks for AI accountability that have not been developed, and there is no liability framework provided when AI is used in diagnosis. Further, Martin et al. (2024) represent that ethical concerns related to patient data privacy and AI biases influence the acceptance of AI among radiologists.

Radiologists can be aided through the development of explainable AI techniques (XAI) to enhance the explainability and Transparency (Marey et al., 2024). Salience maps and SHAP values are visual representation tools to explore the original working and also the decision-making of AI. AI should be regarded as a second reader who can make suggestions, not a definitive diagnosis. Furthermore, radiologists should be trained on AI's strengths and shortcomings, and knowledge should also be disseminated on how to use AI with due care for the generation of data (Debs and Fayad, 2023). Moreover, laying down clear rules for AI accountability can help alleviate such concerns of liability. The fairness and bias mitigation of AI systems can be achieved through regular audits of such systems, which can also increase trust among healthcare professionals. In addition, AI is based on MRI for cancer detection with false positives, false negatives, interpretability, and trust. However, as per Newman-Toker et al. (2021), there are still concerns about missed diagnoses on the part of high false negative rates and overdiagnosis due to high false positive rates, where AI can attain diagnostic accuracy as good as human radiologists. Moreover, the success of AI depends on the accuracy, transparency, and records of Radiologists. However, it can happen due to automation bias, and disbelief afterwards due to algorithm aversion. To increase AI's acceptance and effectiveness, it will be important to improve AI's generalizability and explanation ability, as well as to integrate it into clinical workflows (Ahmad et al., 2021). With human oversight and clinical reliability in place, healthcare systems utilise AI instead of excluding artificial intelligence from the process by creating a collaborative approach whereby AI helps rather than replaces radiologists.

2.4 Analysis of the barriers that occur during AI adoption in MRI-based cancer imaging

MRI-based cancer imaging represents the integration of Artificial Intelligence (AI) that promises to augment the accuracy, efficiency, and early detection of malignancies. However, there exist barriers to the practical adoption of AI in clinical practice (Adler-Milstein et al., 2022). The challenges include institutional barriers like regulatory and liability concerns, and radiologists' views of AI's place in the process of ethical and legal decision-making about patient care. In addition, the acceptance, institutional and professional, of AI in MRI-based cancer imaging is equally important to its technical capabilities (Fransen et al., 2024). Furthermore, the effectiveness of AI for cancer imaging depends on the quality and quantity of MRI data it produces, which is in turn based on its technical capabilities. Moreover, the fundamental impediment to AI in MRI-based cancer imaging is institutional, and strict guidelines are set for the approval and deployment of AI tools in clinical practice by regulatory requirements (Habuza et al., 2021).

Diagnostic models based on AI need to be validated with high rigour and comply with safety requirements before they are approved for large-scale usage. Furthermore, as per Thakkar et al. (2023), many regulatory bodies like the U.S. Food and Drug Administration (FDA) or the European Medicines Agency (EMA) prescribe that AI systems must be reliable, accurate, and consistent in their ability to make medical decisions. It makes it very slow and very expensive to obtain product regulatory approval, and that discourages healthcare providers from spending the money to invest in an AI-driven imaging solution. Another problem it faces is the lack of a standard for AI governance policies among various healthcare systems (Morley et al., 2022). Most of the AI models are built on varied datasets that represent only a portion of the patients.

In addition, clinics and institutions are resistant to developing AI solutions without standard guidelines that guarantee they are safe and effective in other settings and speciality groups (Guidance, 2021). More towards complicating the adoption of AI in MRI-based cancer imaging is the liability, and introducing AI to the diagnostic workflow brings up a key issue of responsibility. Furthermore, legal issues arise once an AI system misdiagnoses a patient or misses malignancies (Evans and Snead, 2024). Radiologists traditionally interpret and make their interpretations, but with AI-assisted diagnostics, there is one new dimension where algorithm error could cause their interpretations. Currently, the legal framework for AI-related errors in radiology is unclear and is leaving the radiologists unsure of what responsibility they have to take when using AI tools (Thieme et al., 2024). This ambiguity also impacts AI adoption because professionals are concerned that they'll be exposed to potential legal ramifications if they're diagnosed wrong.

2.4.1 Regulatory Concerns and Compliance Issues

There is currently fragmentation in the regulatory landscape for AI in MRI-based cancer imaging, for which there is uncertainty on compliance requirements. When it comes to the U.S, if the AI model has access to protected health information (PHI), it needs to comply with the Health Insurance Portability and Accountability Act (HIPAA), and in Europe, if the model can access any data, it has to comply with the General Data Protection Regulation (GDPR) (Konnoth, 2024). As regulations pertain to these AI applications, they lay extremely strict restrictions on data sharing, which makes it difficult for the developers of the AI to build robust and accurate models with the various data needed to train them. Furthermore, the evolution of AI algorithms persists in a continuous manner that constitutes challenges in regulatory oversight. Thus, AI is a dynamic approach, it creates a challenge for regulatory bodies to provide a flexible and stringent approval process (Johnson, 2022). Moreover, regulatory approval complicates whether AI is transparent in making decisions because it lacks transparency. This, consequently, encourages regulatory bodies to hesitate in authorising the use of AI tools that do not have reasonable justifications for the diagnostic outputs of their products, delaying the adoption of AI in MRI-based cancer imaging.

2.4.2 Radiologists' Perceptions of AI's Role in Legal and Ethical Decision-Making

At the current time, the adoption rates of AI are highly dependent on their perceptions of how AI plays a role in legal and ethical decision-making (Kieslich et al., 2022). AI can make image analysis more efficient by automating it and detecting the patterns suggestive of malignancies, but radiologists are relatively hesitant to fully delegate the diagnosis to AI systems. As per Goisauf and Cano Abadía (20220), among radiologists, an important aspect of concern about using AI for medical decision-making relates to ethics. If an AI system is trained with datasets that lack diversity, such as the data it lacks diversity in its data sets such as cancer, then that AI system may not perform well when analysing cancer in a region. This could create unfair treatment of patients, which would violate the ethical principle requiring offering equal health services to all (Giovanola and Tiribelli, 2023). The AI solutions, which radiologists have not been willing to adopt, have not been rigorously tested across different demographic groups for fairness. In addition, the lack of contextual reasoning is the next ethical concern of AI. However, human radiologists interpret MRI scans using clinical context, patient history, and supplementary judgment. On the other hand, AI is based mostly given pattern recognition and statistical correlations. The difference is an issue because AI may lack the means to make ethical decisions when the case is ambiguous or complex (De Bruijn et al., 2022). Radiologists worry that AI would make decisions that are not delivered with humane empathy and a full understanding of the patient's situation to provide comprehensive patient care. This is a particularly sticky problem in any situation where an AI gives unwanted and incorrect advice that results in misdiagnosis.

2.4.3 Trust and Resistance to AI Integration

Trust is one of the major factors that influence radiologists to adopt AI. Resistance is also based on the absence of trust in the reliability, accuracy, and transparency of AI. As per Chen et al. (2021), to have acceptance, radiologists must be able to understand how the AI arrived at its conclusions. Radiologists' increased trust in the AI's decisions is achieved through explainable AI (XAI) techniques, such as attention maps and feature attribution methods, which make AI decision-making more visual. However, there is relatively little adoption of XAI in medical imaging yet, and this increases disbelief about AI (Rosenbacke et al., 2024). One of the reasons for resistance to AI is the fear of displacement in jobs. However, many radiologists fear that the triad of AI will result in falling demand for human diagnosticians. There is no intention by AI researchers to displace radiologists, but job insecurity instigates resistance to employing the aid of AI technologies. This represents that healthcare institutions need to highlight one complementary role of AI in enriching, rather than substituting, human expertise.

2.4.4 Ethical and Legal Frameworks for AI Implementation

Guidelines for AI accountability, patient consent, and mitigating bias can help to set the radiologists' concerns at rest. Legal frameworks should delineate liability structures in terms of who is responsible for errors in the AI and AI-related diagnosis (Evans, 2023). Moreover, the formulation of ethical standards in AI development aims at fairness for stakeholders and transparency in medical imaging. On the other hand, AI's recommendations and the implications they have on patient autonomy should also be taken into consideration in ethical considerations. However, many AI systems do not have to explain their ability, so patients have the right to understand how their diagnoses are determined (Amann et al., 2022). AI-generated decisions derived from imaging can be made interpretable to enhance patient trust and adoption of AI imaging. Existing barriers to the adoption of AI for MRI-based cancer imaging include institutional barriers, regulatory concerns, liability issues, and radiologists' perception of the ethical and legal implications of AI (Durur-Subasi and Özçelik, 2023). For the acceptance of AI in medical imaging, trust and transparency are required. These barriers are addressed through multiple angles, including regulatory reform, Explainable AI model development, and Ethical guidelines preventing fairness and accountability. By surmounting these hurdles, AI can be made to contribute beneficially to MRI-based cancer imaging in enhancing diagnostic accuracy and improving patient outcomes.

2.5 Impact of AI-assisted MRI on workflow efficiency and cognitive workload

Magnetic resonance imaging (MRI) is most integrally changed by AI integration, as it has significantly altered MRI workflow efficiency and reduced radiologists' cognitive workload. AI-driven MRI systems are designed to reduce time and manual work in the diagnostic process, reduce manual work, and increase accuracy (Van Leeuwen et al., 2022). However, as per Ahn et al. (2022), the efficiency of AI in image analysis is the cause for such concern, as it requires radiologists to look over AI-generated outputs. Furthermore, it is important to consider the effects of AI on radiologists' stress levels and burnout to fully judge the overall effect. Widespread popular recognition of AI-assisted MRI systems as enhancing workflow efficiency has also realised that MRI interpretation is traditionally a time-intensive process that is subject to diagnostic accuracy (Tong et al., 2025). With AI, this workflow is automated by image processing, finding anomalies, and pointing out possible malignancies. Furthermore, AI can cut down the time from image interpretation, freeing radiologists' time for more complex cases to deal with. The accuracy of the AI-assisted diagnostic models was not affected, but such models reduced image interpretation time by nearly 30% in breast cancer screening (Carriero et al., 2024). AI could just as easily analyse lung MRI scans as quickly and as well as experienced radiologists to detect cancerous lesions. A typical radiologist does not have the time to attend every doctor's appointment, and second, typing a preliminary diagnosis is time-consuming. The enhancements improve patient throughout and reduce the delays in diagnosis and treatment plans, respectively.

AI increases the speed of decision-making, leading to accelerated MRI interpretation and boosting productivity for radiology departments (Pierre et al., 2023). Although AI is designed to relieve the radiologists' load, its sustainability might bring new challenges in the context of verification and oversight. The diagnosing AI needs to be reviewed and validated by human radiologists to be accurate, which can be an additional cognitive burden rather than a relief (Larson et al., 2021). Moreover, Radiologists necessarily spend more time checking AI predictions with clinical findings, even though AI expedites image analysis. According to Mata et al. (2021), it was found that AI-assisted MRI helped increase sensitivity in prostate cancer detection but enhanced cognitive load to the radiologists as they needed to confirm AI-generated outputs. In addition, the complication of the verification process is worsened by automation bias, which is the phenomenon that clinicians follow AI recommendations.

2.5.1 Influence of AI Integration on Radiologists' Stress Levels and Burnout Risk

Working conditions in radiology are very stressful and tend to cause a high percentage of burnout, so radiologists are predisposed to stress and burnout. Mental fatigue is also brought about by high caseloads, time constraints, and diagnostic responsibility factors (Nichols et al., 2022). It mitigates as much or exacerbates stress in radiology workflows, depending on how AI is introduced into such workflows. The proponents of AI say that the potential of AI to automate mundane jobs reduces workload and fatigue. A lot of repetitive work in MRI interpretation can be handled by AI and allowing radiologists to spend more time on complex cases. Moreover, AI can help reduce the frequency of diagnostic errors and give radiologists more confidence in their assessment (Zhang et al., 2023). AI accompanying MRI readings lowered the rate of missed diagnosis and was accompanied by a reduction of the subjective level of fear imposed by the fear of medical errors. In addition, AI integration also brings its challenges that could add more stress to the daily work of companies and their employees (Huang and Gursoy, 2024). Added demands are required for constant verification, due and the unpredictable nature of the performance of AI. When AI outputs clash with radiologists' clinical judgments, the radiologists find themselves in doubt regarding which diagnosis to trust. More than 43% of the radiologists felt that the working environment would be more stressful when they encountered the mode of AI-assisted MRI and highlighted the issues relating to the liabilities and possibility of misdiagnoses (Adler-Milstein et al., 2022). Additionally, training radiologists to adapt to AI systems is an additional burden on their workload and can lead to burnout. One of their concerns is the fear of being replaced by the job. Despite being supposed to be a complement to human expertise rather than a replacement, some radiologists feel that greater automation may render them superfluous, and there is a fear of adoption in the workplace, stress.

2.5.2 Striking a Balance: Optimising AI for Enhanced Workflow and Reduced Burnout

A balanced approach to integrating AI is needed to make its benefits realised as much as possible while minimising its drawbacks. The position of AI as a tool to assist radiologists in their efficiency should be better placed as being viewed as an autonomous decision-maker (Lombi and Rossero, 2024). Radiologists' uncertainty and stress are alleviated by AI models that are transparent and have explainable decision pathways. Without explanation, radiologists never trust the results of an automated AI scoring system and always need to go back and verify the significance of the input features that lead to an outcome. For the refinement of AI systems against clinical workflow, close collaboration is needed between AI developers and radiologists (Taribagil et al., 2023). AI model training should involve radiologists, as they should actively contribute to making AI algorithms align with real-world diagnostic challenges. Additionally, AI training programs need to prepare radiologists for the ability to read and verify the findings produced by AI. Moreover, as per Crotty et al. (2024), when AI education is integrated into radiology curricula, institutions can give radiologists the proficiency to work with AI and decrease the cognitive load that would come if they were learning something new. AI must also be applied to the implementation of strategies for workload redistribution amongst healthcare institutions. MRI scans can be pre-screened by AI, and only those with high risk are flagged for radiologists' review (Zhang et al., 2024). The targeted strategy can facilitate managing the load of the radiologists and help in reducing fatigue and enhancing diagnostic accuracy. More conducive to the workflow is the use of models for structured AI-human collaboration, including dual reader approaches where AI is utilised as a secondary reviewer to avoid AI-based overburdening of radiologists. To counter the stress and social issues, the ethical and legal implications of AI in MRI interpretation must also be considered (Shen et al., 2024). Moreover, Standards of AI governance should come up with standardised protocols for it to be overseen by someone else, rather than the radiological faculty alone. To increase confidence in AI and facilitate its responsible use, implement safeguards such as AI audit trails and performance monitoring systems.

2.6 Conceptual Framework

The conceptual framework is a structure that allows the research to be guided through the linkage of existing theoretical knowledge to research questions, methodology, and findings. Finally, it places the study within the larger academic discourse, which means that the non-research will contribute to extant theories while acknowledging the areas where further research could be conducted to contribute to theory development. This conceptual framework is useful in the context of bringing AI into MRI-based cancer imaging, explaining key concepts, associating ideas, and providing an explanatory model for data analysis. The first function of the conceptual framework contributes to defining the main concepts to be used in the research. The field of AI-assisted MRI is rapidly evolving and has a nexus with different domains such as radiology, healthcare technology, ethics, and cognitive workload (Tariq, 2025). This research examines the concept of AI accuracy, interpretability, radiologists' trust, workflow efficiency, cognitive workload, stress levels, and institutional barriers to the adoption of AI. Furthermore, it is used as an analytical tool to study the effect of AI integration on the professional experiences and decision-making of radiologists. The study further adopts theoretical frameworks like the Technology Acceptance Model (TAM) and Socio-Technical Systems Theory (STS) to explain human adoption and processes between AI technology and human decision-making or redoing in the clinical settings (Passalacqua et al., 2024).

Figure 1: Conceptual Framework

This research investigates one of the most important relationships, namely, the relationship between radiologists' trust and AI accuracy. Due to high false-positive or false-negative rates, it is possible that radiologists will not adopt AI models into routine diagnostics. Thus, in this relationship, algorithm interpretability plays a role as a mediator, and better explainable AI (XAI) facilitates trust and usability (Shin, 2021). Furthermore, the framework will evaluate how cognitive workload is affected by the AI-driven workflow efficiencies because of the requirement for human verification, AI may do away with repetitive tasks and diagnosis, but at the expense of greater cognitive demands on radiologists. Additionally, the conceptual framework allows data analysis to be explained in terms of patterns and connections. The research can use theoretical models to ascertain whether AI integration fits with current technology acceptance theories or is novel enough to warrant modifications of theoretical perspectives. Moreover, it leads to the finding that AI is increasing cognitive workload, and not reducing it, which could be at odds with views as to automation and efficiency in healthcare. Moreover, the rising adoption of AI may be suppressing rather than boosting the adoption of AI by radiologists due to liability issues versus technical problems. Therefore, they provide evidence for refining or extending theories of AI adoption within radiology. The conceptual framework helps in determining existing gaps in current theoretical principles. If the observed data patterns do not fit within extant theories, this research will add to theory development by proposing modifications or the development of new explanatory models. The iterative process is not only based on existing literature but also contributes to the expansion of knowledge by refining theoretical constructs. This framework encompasses how established theories can take the bulk of the empirical findings of AI adoption in MRI-based cancer imaging and the structured approach.

2.7 Chapter Summary

The above chapter represents the ability of AI to perform well with a level of diagnostic accuracy improvement, a reduction in the radiologists' workload, and an improved workflow efficiency. However, there is a lot of concern regarding the rate of false positives as well as false negatives, cognitive burden because of verification requirements, regulatory and liability issues, and trust in AI on the part of radiologists. The above review also highlights how much AI affects stress levels, jeopardises a radiologist's career through burnout, and highlights the necessity of well-balanced AI integration strategies. Moreover, the Technology Acceptance Model (TAM) and Socio-Technical Systems Theory (STS) help to fill gaps in understanding the shaping of clinical decision-making by AI. For transparency in the AI models, proper regulatory guidelines, and training programs for AI models, make AI an assistive tool and not a replacement for radiologists. To connect the technological improvements of AI with its field of application in clinical practice, interpretability needs to be improved, regulators should give clarity, and AI developers and healthcare professionals need to collaborate. Moreover, in this chapter, current literature on the use of AI-supported MRI in early cancer detection was critically reviewed concerning diagnostic accuracy, cognitive workload, radiologists' trust, and ethical, legal, and regulatory considerations for AI integration. However, it was clear that AI can strongly increase workflow efficiency as well as early cancer detection rates, but still, about trust, interpretability, and bias in diagnostic outputs. Additionally, factors such as automation bias, algorithm aversion, and cognitive load impact radiologists' acceptance of AI in clinical practice. Real-world studies of radiologists' real-life experience are a key gap and one of the institutional barriers to AI integration. Based on this, there is a need for the collection of primary data through means such as the use of questionnaires and interviews. The research methodology to fill these gaps will be outlined in the next chapter; specifically, the design of the approach is mixed methods, data collection techniques, and ethical considerations that align with academic rigour and participant protection.

Chapter 3: Research Methodology

3.1 Introduction

At the current time, AI use is increasing rapidly, and most of the healthcare sector integrates AI into their process to increase the detection rate and decision-making. This work aims to evaluate the impact of the AI-assisted MRI approach in the early detection of cancer. This chapter is the methodology chapter, which provides detailed information about the approaches that help to collect and evaluate the information. In addition, in this chapter, the research onion model is considered, which assists in determining the step-by-step approaches significantly.

3.2 Research Philosophy

At the current time, the identification of an accurate methodological approach is one of the major concerns that occurs in front of researchers face during the study and directly impacts the significance of the research. To overcome this barrier, a research onion model has been considered, which not only provides the information related to methodological approaches but also provides a structured process for the study. According to the model, the research philosophy is the first phase of the research, which helps the researchers to identify the direction of the study (Saliya, 2023). The research philosophy is a combination of interpretivism, positivism, realism, and pragmatism. However, as per Bergmann (2023), the selection of the philosophy based on the research type is one of the major issues faced by the researchers and impacts the study's significance.

This work aims to analyse the role of the AI-assisted MRI in the early detection of cancer. This study is focused on primary research in which quantitative and qualitative data are considered. Therefore, the pragmatism philosophy has been employed in this study to conduct the research. It is one of the philosophies that provides an accurate path for the research and helps to conduct the primary study based on qualitative and quantitative information (Shan, 2022). In addition, this helps to collect the information which is not been used by any researchers previously and helps to justify the research goals with the help of scientific and quantifiable phenomena. Thus, pragmatism philosophy helps to collect the primary information which helps to determine the role of the AI in radiologist work and trust in AI and trust in AI.

3.3 Research Approach

In research, the identification of the research nature is one more concern that occurs in front of the researcher at the time of study. As per the research onion model, the research approach is a methodological approach that helps the researchers to develop a research question and hypothesis based on the study objective significantly (Proudfoot, 2023). According to the model, it is the combination of the inductive approach and the deductive approach. The inductive represents the formation of the research question, and the deductive represents the formation of the research hypothesis (Haque, 2022). However, this work contains mixed philosophy, which represents the consideration of qualitative as well as quantitative information.

Therefore, during the research, both approaches are applied, which means that in this work, both the research question and hypothesis are developed based on the research objective. The inductive approach helps to form the research question “How do radiologists perceive the trustworthiness and workflow impact of AI-assisted MRI in early cancer detection?” and the deductive approach helps to form the research hypothesis such as “When AI-assisted MRI models are easily explained and included into workflow procedures, radiologists are more likely to accept the technology” and “The use of AI in radiology is adversely affected by worries about interpretability, dependability, and workflow disturbances”. Therefore, it represents that the combination of both approaches helps to identify how AI-assisted MRI helps the radiologist in early cancer detection and helps to determine the impact of trust in AI on the adoption of AI-assisted MRI.

3.4 Research Choice

At the current time, the selection of the nature of the data is one of the major aspects considered by most researchers to complete the study efficiently. In addition, the research choice is one of the methodological approaches that helps the researcher develop a structured process to extract the information according to the study's nature (Nanthagopan, 2021). The research onion model represents that research choice is the combination of three sub-choices, like Mono, Multi, and Mixed. The mono represents the collection of one type of information, and the multi or mixed choice represents the consideration of multi-nature information during the collection of relevant data (Ganesha and Aithal, 2022).

This work aims to analyse the role of AI-assisted MRI in early cancer detection and help to identify how it impacts the radiologist's trust and decision-making. To achieve the objective of the study, the primary data is considered. Therefore, mixed research methods have been applied in this work, which represents that to achieve the objective study qualitative and quantitative information are considered. These combinations of information help to explore radiologists' decision-making processes, cognitive biases, and measure radiologists’ trust, AI adoption, and workflow impact efficiently.

3.5 Research Strategy

In research, the nature of the data plays an important role in justifying the research objectives. The research strategy is one of the methodological aspects that helps to determine the nature of the information in a significant manner (Islam and Aldaihani, 2022). The research onion model represents that the research strategy is the sum of different techniques, such as Survey, Interview, literature review, descriptive, Case study, and SLR, which are adopted by the researchers based on the type of study (Johannesson et al., 2021). However, the implementation of the research strategy, which is linked to the objective, is one of the major concerns that occurs in front of the researchers and impacts the study's significance.

Therefore, this work aims to determine the role of the AI-assisted MRI approach in early cancer detection. In addition, in this work, mixed methods are considered, which represent the consideration of both qualitative and quantitative information. Therefore, in the case of quantitative information, a survey research strategy is applied, and in the case of qualitative information, an interview research strategy is considered. These strategies help to determine the radiologist's trust in AI and help to identify how AI helps the radiologist to improve decision-making ability during early cancer detection. Furthermore, these help to determine that is use of AI-assisted MRI is helpful in the detection of cancer and helps to improve work efficiency.

3.6 Time Horizon

The selection of the time frame is one of the aspects considered by the researchers to maintain the reliability and credibility of the study. The onion model represents that the time horizon is the 5 layers and was adopted by the researchers during the collection of information. The cross-sectional and longitudinal are time horizon approaches considered by the researchers according to the study. The cross-sectional represents that information has been collected at a single point in time, and the longitudinal represents the collection of information at multiple points in time (Ismail et al., 2022). However, in the case of longitudinal data, the data storage, authenticity, credibility, and reliability challenges occur, which directly impact the significance of the study. Therefore, in this work, the cross-sectional time horizon approach is considered in this work which represents the survey and interview information assembled at a single point in time. This helps to complete the work significantly and helps to identify the role of AI in MRI on radiologist decision-making, trust, and early detection.

3.7 Data Collection

The selection of accurate information sources and the extraction of relevant information from the sources are the major aspect that helps to complete the study. However, the selection of an accurate data collection technique is one of the major issues faced by most researchers. To overcome this barrier, the onion model is considered, which states that the research techniques are the second-to-last layer and provide the information related to the data collection technique. In addition, the model represents that primary data collection and secondary data collection are the major techniques adopted by the researchers to collect the information (Dawadi et al., 2021). The primary technique represents the consideration of information which is not been used by any researchers previously, and this information has never been published on any platform. The secondary techniques represent the consideration of pre-published information. However, as per Khan and MacEachen (2022), in the case of the secondary technique, authenticity and credibility challenges occur, which may impact the research significance.

This work aims to analyse how AI-assisted MRI in the early detection of cancer helps radiologists improve their decision-making and how trust in AI impacts the adoption of AI-assisted MRI in cancer detection. Thus, to achieve the goal of the study, the primary data has been considered, in which both qualitative and quantitative information are considered. To collect the quantitative primary information, a survey strategy is considered. During the survey, a structured questionnaire using Likert scale responses (1-5) is considered, which helps to measure trust, interpretability concerns, and perceived AI benefits/barriers. However, the distribution of the questionnaire is one of the major issues faced by the researchers. To overcome this barrier, a person-centred approach as a sampling process is considered in which the developed questionnaires are distributed via radiology professional networks and LinkedIn groups. In this case, the survey has been distributed to 50-100 Health professionals specialising in oncology and diagnostic imaging. Therefore, this data collection technique helps to measure radiologists' trust, AI adoption, and workflow impact. Moreover, in the case of qualitative data collection, an interview strategy is considered in which open-ended questions are developed and Semi-structured interviews with health care professionals. During the interview, a Snowball sampling approach is considered, which represents that the participant collection starts with known radiologists and expands via professional referrals. In addition, it is ensured that selected participants are Board-certified and work in oncology and diagnostic imaging. The participants have a minimum of 1 year of clinical experience with MRI-based detection, and participants are currently working on AI-assisted MRI tools. However, in this case, it is ensured that those participants are not considered who do not know the AI-assisted MRI tools and AI developers who have no clinical background in radiology are not considered. Moreover, during the interview, 4 radiologists from hospitals and diagnostic centres with AI-integrated MRI systems are considered and conduct Virtual or face-to-face 30-45 min interviews. Therefore, it represents that these are the major data collection techniques applied in this study to assemble the relevant information ethically.

3.8 Data Analysis

The research procedure taken by the researchers is also one of the aspects that allows the analysis of the assembled information to justify the research objectives and provide an interpretation of the findings. However, in most of the studies, the researchers had problems in choosing the analysis approaches of the chosen data, and problems with the chosen approaches linking the study (Ghanad, 2023). Qualitative and quantitative methods are proven to be two processes during data analysis. For the qualitative information in the qualitative procedure, different analytical approaches such as thematic analysis, literature analysis, content analysis, and case study analysis have been used to assess the qualitative procedure. Further, the quantitative procedure is the evaluation of the quantitative information with the use of descriptive statistics, inferential statistics, and experimental analysis (Mishra and Alok, 2022). In this work, mixed research methods are under study, comprising both qualitative and quantitative information. For quantitative analysis (survey) then descriptive analysis and inferential analysis are used. The Mean & Standard Deviation for trust levels, perceived AI benefits, and workflow efficiency scores are included in it. Furthermore, the quantitative information is assessed utilising the Chi-square test and Pearson correlation analysis. The SPSS analytical tool is to be used for such tests to evaluate the research hypothesis.

Moreover, during the analysis of the interview information (qualitative), the thematic analysis has been considered. The thematic analysis is one of the procedures in which common themes are developed based on the objectives, which not only helps to justify the objective but also helps to achieve the goal of the study. Furthermore, during the thematic analysis, common themes are developed based on the semi-structured interview and research objectives such as "*analysis of radiologists' trust levels in AI-powered MRI for early cancer detection", "Comparision of AI's perceived accuracy and reliability compared to human radiologists", "Analysis of the challenges* *faced radiologist during AI adoption in MRI-based cancer imaging", and "Impact of AI-assisted MRI on workflow efficiency and cognitive workload".* Therefore, it represents that these are the major analysis procedures applied in this work to evaluate the assembled information ethically.

3.9 Ethical Consideration

This mixed-method research takes ethical considerations central to the integrity and credibility of this research. Throughout the study, informed consent and confidentiality are prioritised. A detailed information sheet including the research purpose, methodology, data usage, and assurances of confidentiality is given to all participants. Data collection must be entirely voluntary, with written or electronic consent provided before being subjected to data collection. To protect participants' privacy, all data are anonymised and no identities will be published or shared (Cash et al., 2022). Furthermore, during the study, obtain ethical approval from the relevant institutional ethics committee to guarantee that all GDPR and Declaration of Helsinki ethical standards are being met. Moreover, various steps are taken to counteract any possible bias of the researcher and enhance the quality of the research. The survey questions and interview prompts are designed with neutral, non-leading language so that there is no influence on how participants respond. In addition, the themes of disbelief about AI will be dealt with impartially to shed a balanced light on things (Khogali and Mekid, 2023). This rigorous ethical framework is designed to ensure the Rights, Dignity, and Privacy of all participants at the same time respects academic transparency as well as accountability during the research process.

3.10 Chapter Summary

The above chapter is a research methodology section that provides information about the main methodological approaches that are necessary for the study. This work aims to analyse the role of AI-assisted MRI in the early detection of cancer. As per the above analysis, it is identified that pragmatism philosophy, mixed research approach, mixed strategy, cross-sectional time horizon approach, and mixed choice are considered, which helps to determine the appropriate structure for the study. Moreover, the survey and interview were conducted in this work to collect the information. In addition to this quantitative analysis, with the help of the SPSS tool, and qualitative analysis with the help of a thematic approach is conducted, which helps to complete the study efficiently.

Chapter 4: Results, Findings, and Discussion

Overview

The statistical information obtained through an SPSS analysis of survey data is presented in this Chapter from radiologists, oncologists, imaging specialists, and AI researchers. The analysis contains descriptive statistics alongside frequency distributions, together with complex inferential tests which use correlation analysis, ANOVA, chi-square and t-test, and multiple regression. This research section methodically explains what participants think about AI-supported MRI evaluation of diagnostic precision regarding work management, stress levels, trust measures, ethical considerations, and regulatory awareness. The analysis follows its designated research objectives and hypotheses and provides quantitative evidence, which is illustrated using charts and tables to enhance understanding.

Further, while the Discussion Chapter will analyse the study results regarding the main research inquiry and formulate hypotheses using SPSS statistics, interview analysis, along with research literature. The analysis examines how radiologists trust AI for MRI assistance, along with its precision rate and reveals obstacles to implementation and workflow relationship and burnout effects. Hospitals can harness AI-driven diagnostic capabilities effectively, yet implementation is limited by healthcare providers who seek AI explanation methods alongside legal risk assessments and reduced cognitive strain during workdays. The Chapter demonstrates the significance of TAM and STS theoretical frameworks in studying radiology professionals' behaviour toward technological integration as well as human-machine functional bonds.

4.1 Quantitative Analysis

4.1.1 Demographic Profile of Respondents

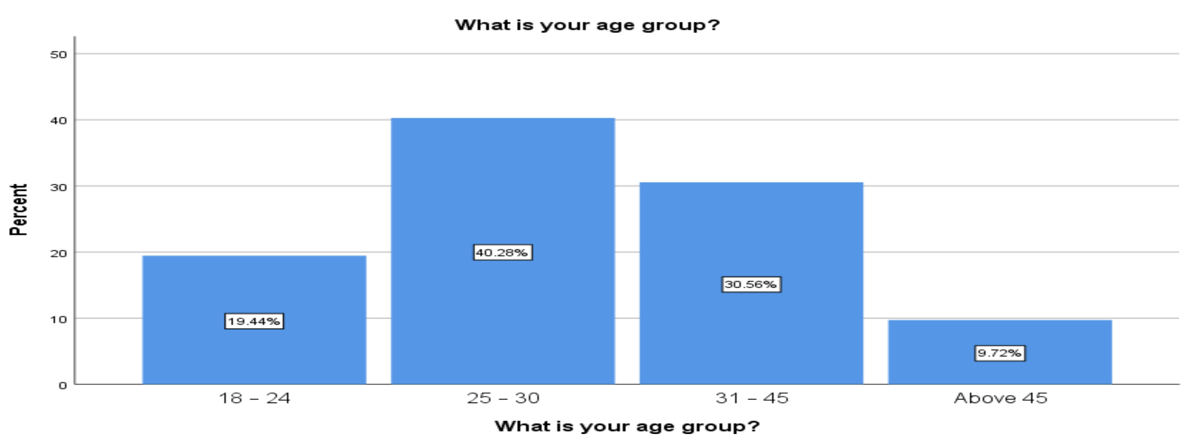


Figure 2: Age Distribution of Respondents

A total of 72 practitioners who work in the medical imaging and oncology sectors provided their responses for this study. The most numerous respondents belong to the young professional age range, spanning from 25 to 30 years old (40.28%), while those between 31 and 45 years constituted another substantial group (30.56%). Most study participants were aged 18 to 24 years among the 72 professionals who completed the survey. Senior professionals represented less than 10% of the total respondents.

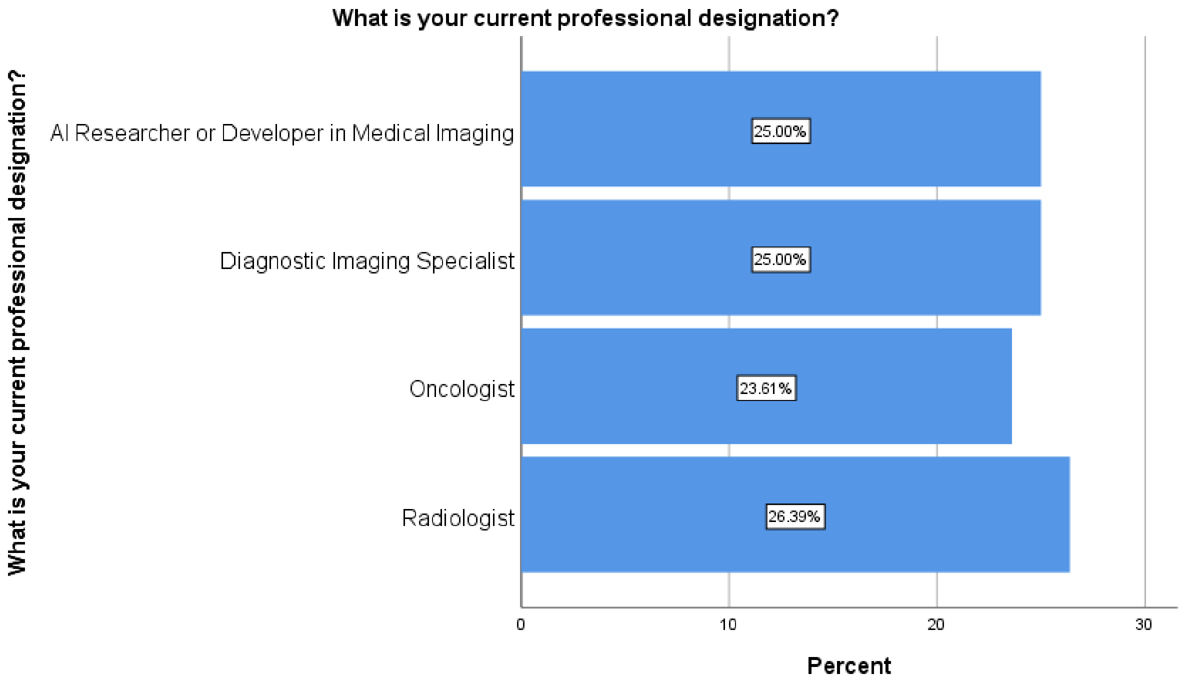


Figure 3: Professional Designation of Respondents

Among all professional groupings, the sample included a comparable distribution where 26.39% were radiologists, while diagnostic imaging specialists made up 25% and medical imaging AI researchers accounted for another 25%. 23.61% of the participants who identified as Oncologists demonstrated substantial numbers among both clinical practitioners and AI-oriented professionals.

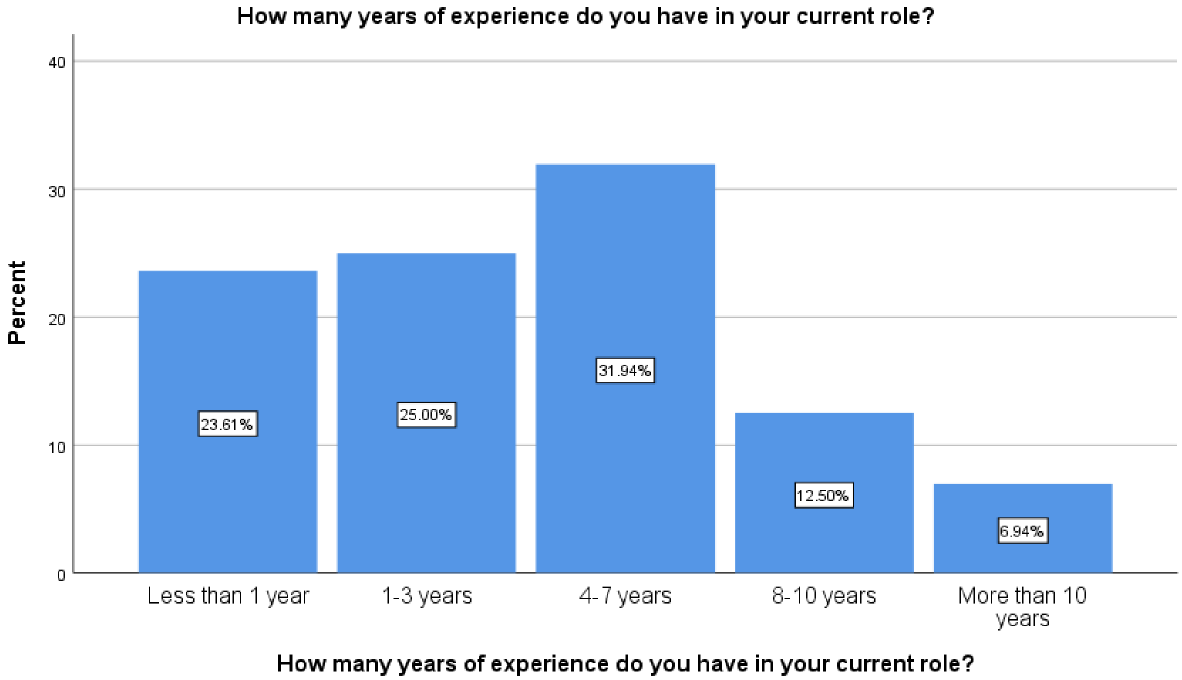


Figure 4: Years of Experience in Current Role

During the survey, more than 80% of respondents reported spending less than eight years in their current position, with 31.94% working 4–7 years, 25% working 1–3 years and 23.61% reporting less than a year of experience. Among the participants who completed 8–10 years or more than 10 years of work experience, 12.5% and 6.94% comprised the total. The survey participants mainly comprised health professionals who were early to mid-career stage with equal skills in clinical work and technical domains, thereby providing suitable insights about AI-assisted MRI in modern practice settings.

4.1.2 AI-Assisted MRI Familiarity and Usage Patterns

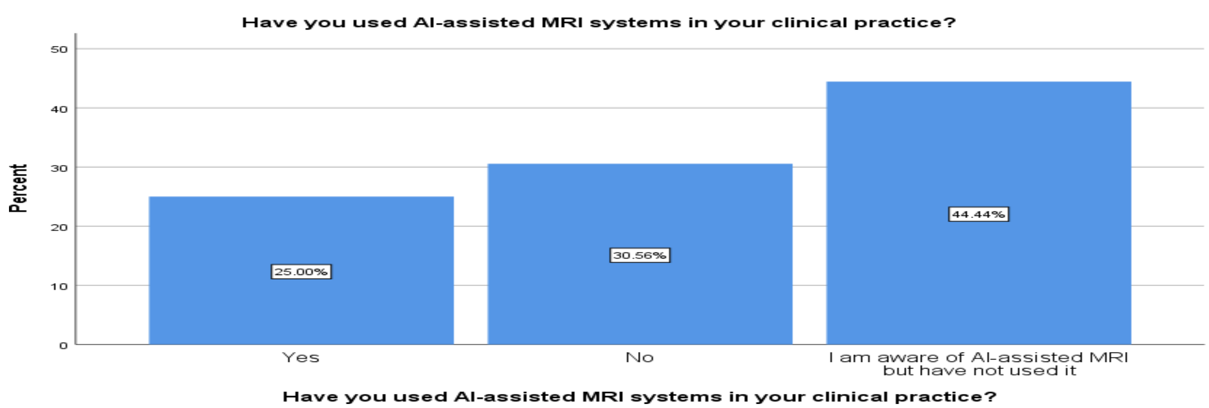


Figure 5: Familiarity with AI-Assisted MRI

The research shows that professionals demonstrate different levels of contact with AI-assisted MRI systems. About one-quarter of these professionals revealed clinical use of AI-assisted MRI systems, yet three-tenths had never applied them. The biggest demographic group, consisting of 44.44%, demonstrated knowledge about AI-assisted MRI systems even though they had not utilised them.

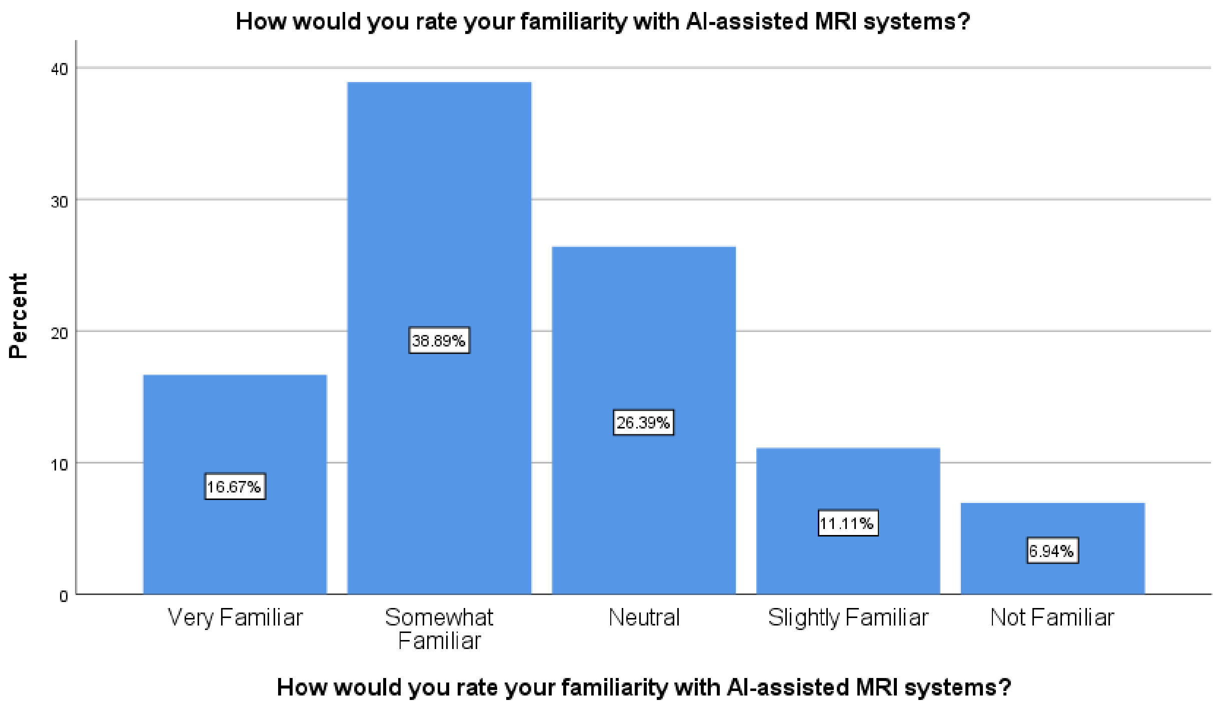


Figure 6: Usage of AI-Assisted MRI in Clinical Practice

Studies demonstrated that around 38.89% of participants felt somewhat familiar with AI-assisted MRI tools, while the same percentage (16.67%) identified as thoroughly knowledgeable about them. This data shows an average level of understanding among participants. The surveyed population maintained a neutral response to AI-assisted MRI tools at 26.39%, while 11.11% expressed slight familiarity and 6.94% declared no familiarity. The rising awareness levels show progress, yet practitioners require enhanced hands-on learning opportunities and practical training to achieve higher confidence and improved real-world applications. The findings reveal that awareness about AI lacks sufficient practical groundwork to drive adoption, thus demanding formal training programs for enhancing clinical adoption of AI tools. The gathered data provides essential knowledge to create AI implementations and the operational implementation infrastructure within radiology procedures.

4.1.3 Perceptions of AI-Assisted MRI Benefits and Workflow Impact

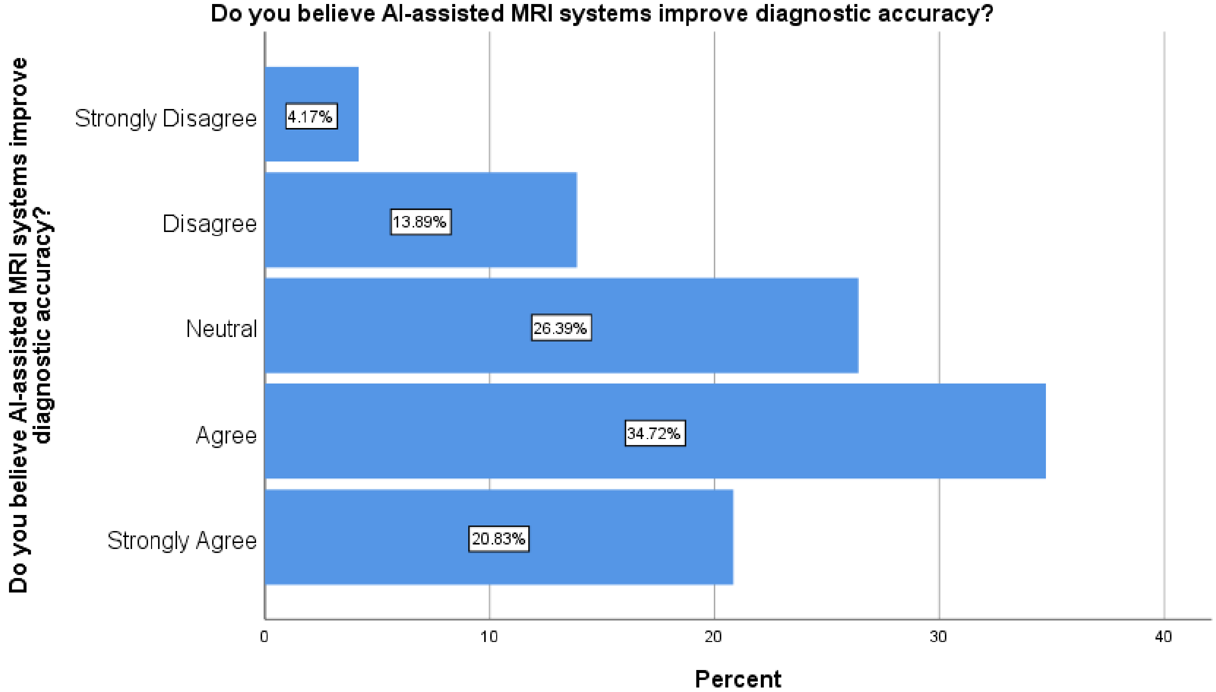


Figure 7: Perception of Diagnostic Accuracy Improvement

The majority of medical practitioners have positive views about how AI systems improve diagnostic accuracy for MRI assessments. The research findings showed that AI diagnostic systems received endorsement from 34.72% of participants who agreed with them and 20.83% who strongly agreed with their precision improvements. The findings show that half of the participants believe artificial intelligence demonstrates effectiveness during radiological evaluations, especially for detecting early cancers. The survey revealed a minority distrust of AI reliability because 13.89% disagreed and 4.17% strongly disagreed with its use. Results-driven outcomes remain unclear, or doctors have restricted exposure to such results, as indicated by their 26.39% neutral response rate.

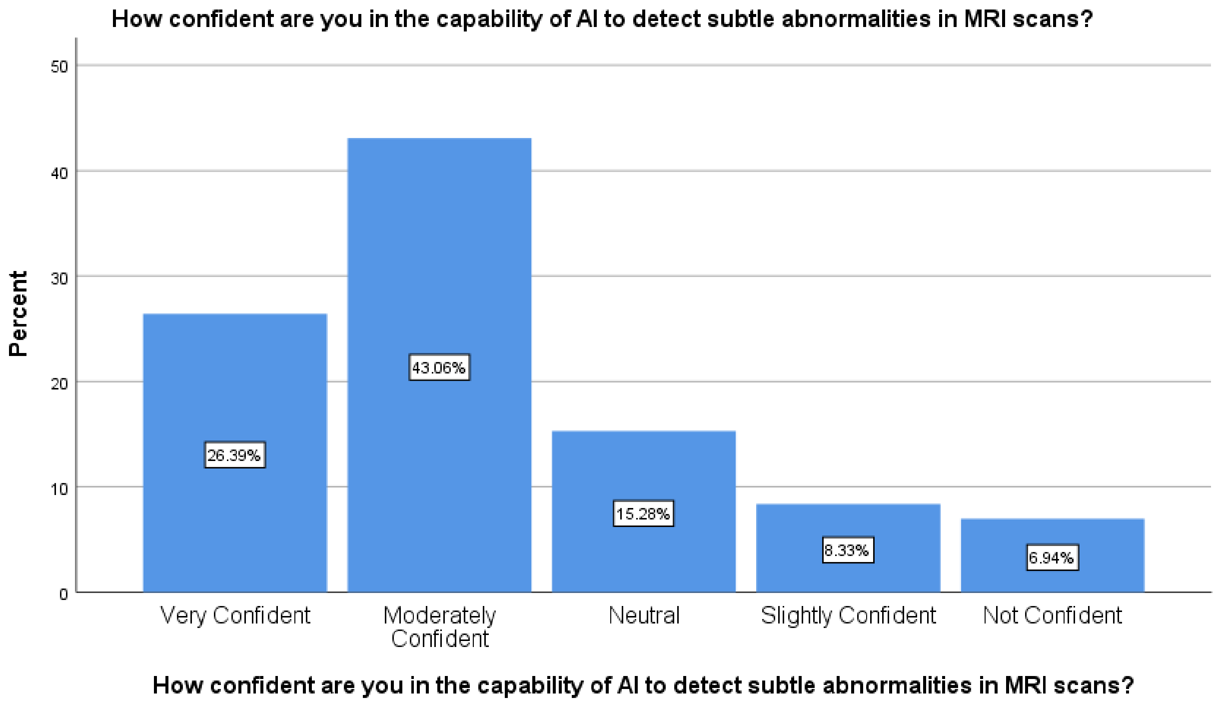


Figure 8: Confidence in AI Detecting Subtle Abnormalities

A large portion of 43.06% indicated moderate confidence, alongside 26.39% expressing strong confidence in AI detection of minor abnormalities within the imaging scans. The responses displayed that 8.33% of participants had moderate confidence, while 6.94% exhibited no confidence in AI's detection capabilities. The 15.28% group displaying neutrality includes respondents who lack practical experience in this field. A significant number of healthcare professionals now believe that artificial intelligence achieves superior sensitivity for diagnosing small lesions, together with early-stage tumours.

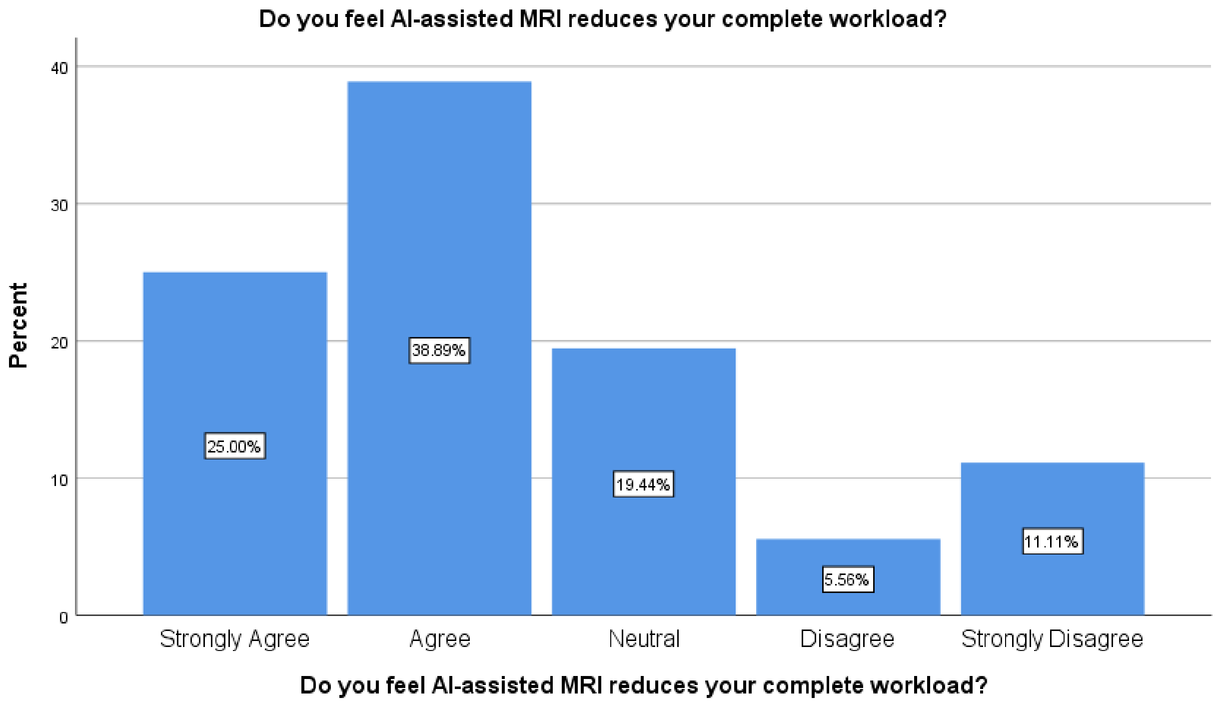


Figure 9: AI’s Impact on Radiologist Workload

The provided graphic shows medical expert evaluations regarding the effect of AI support systems on their overall workload. Most professionals demonstrated positive outlooks about AI's reduction of workload since 38.89% agreed and 25% strongly agreed, which totals up to 64% of responders. The research confirms that AI operates successfully in repetitive work, including image segmentation and preliminary scan analysis tasks. A significant portion, totalling 19.44%, showed moderate insights about AI's operational effects while keeping a neutral stance. Few respondents who disagreed with 5.56% or strongly disagreed with 11.11% showed reluctance toward AI technology, possibly due to their fears of extra verification work and workflow interference. Most professionals regard AI-assisted MRI as an efficiency-boosting tool that saves time, according to the gathered data. The occurrence of negative and neutral responses indicates that medical professionals require improved AI implementation with more obvious clinical benefits to demonstrate. Organised AI implementation strategies should lead to increased user perceptions of value in MRI systems.

Figure 10: Time Savings for Complex Cases

As a sample group of radiologists approved of the statement that AI supports complex case reviews by freeing up more time. A total of 37.5% showed agreement and 18.06% strongly supported the point, while 26.39% maintained a neutral stance and 18.06% (disagree + strongly disagree) expressed dissent. The survey results show that AI is perceived as time-saving by numerous doctors, yet there are medical institutions where the technology might not generate efficient time benefits.

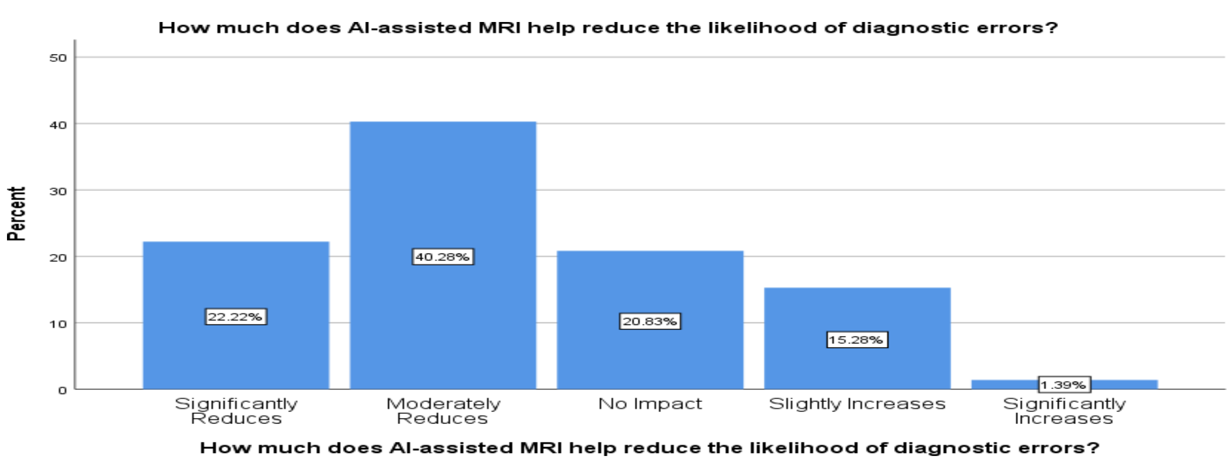


Figure 11: Reduction in Diagnostic Errors

The majority of 62.5% of respondents believe that AI reduces diagnostic errors at either a significant level of 22.22% or a moderate level of 40.28%. A small percentage of 1.39% maintained that the use of AI technology leads to an important increase in diagnostic mistakes. Widespread confidence emerges from the fact that artificial intelligence provides extremely precise analytical abilities, which reduce both false negatives and minor oversight scenarios.

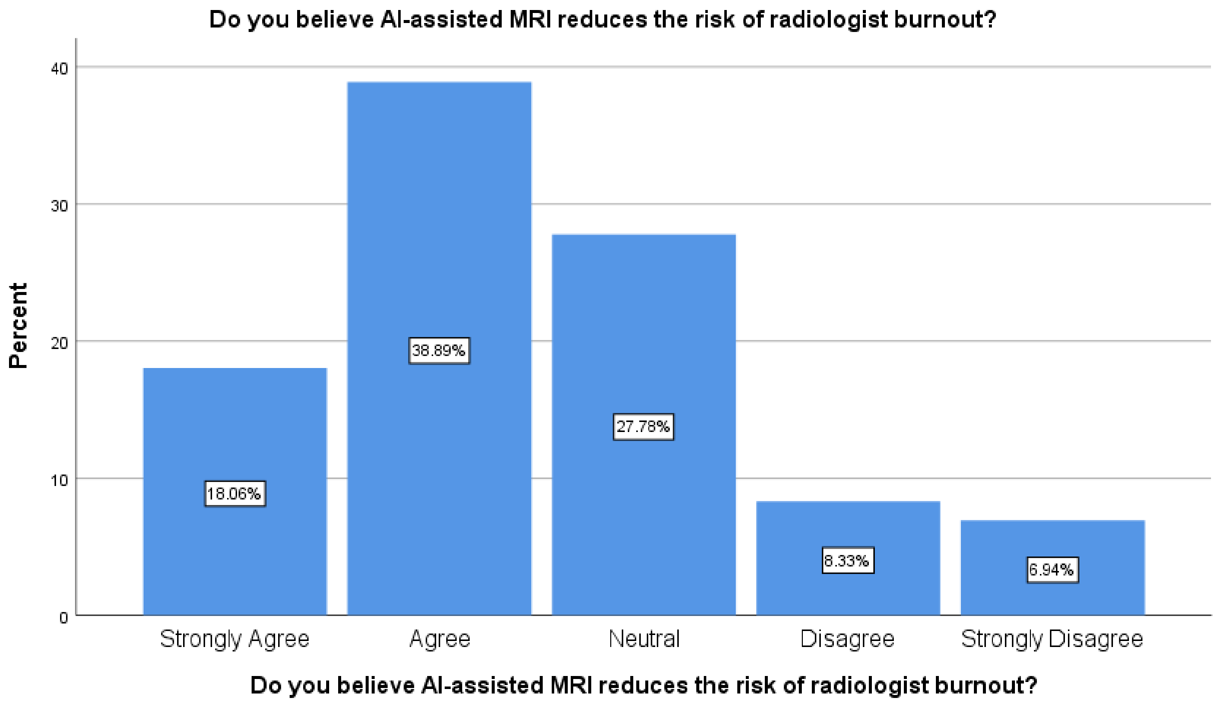


Figure 12: Burnout Risk Reduction

A majority of 57.95% among the respondents endorsed the opinion that AI technology supports risk reduction for radiologist burnout, while 18.06% strongly concurred with this belief. The data reveals AI's effectiveness in decreasing stress levels through the reduction of high image analysis volumes, since only 15.27% of respondents showed disagreement.

4.1.4 Trust, Barriers, and Adoption Drivers

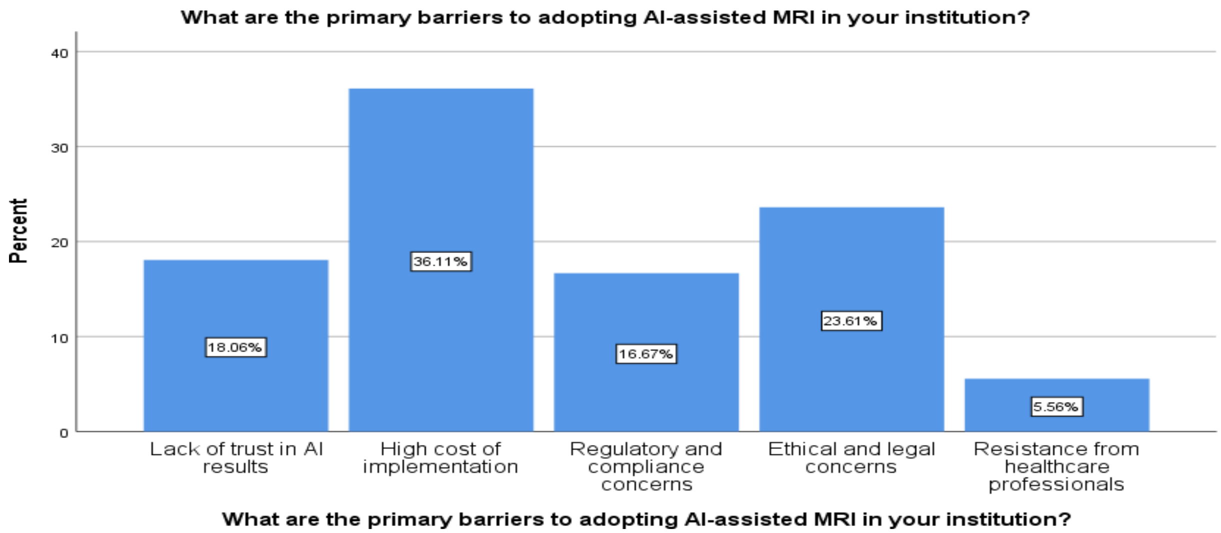


Figure 13: Perceived Barriers to AI Adoption

The data analysis from SPSS demonstrates multiple important factors which help or hinder the commitment of clinical staff to use AI-assisted MRI technology. The high expenses of implementation serve as the main obstacle, according to 36.11% of survey participants. The challenges with infrastructure development, together with integration obstacles, form the core obstacles identified by the respondents. The adoption barrier of ethical and legal concerns was identified by 23.61% of respondents, while trust issues with AI results affected 18.06% of them. The adoption of AI-assisted MRI faced two significant barriers, which were regulatory and compliance concerns and healthcare professional resistance, although these scenarios occurred less frequently (16.67% and 5.56%, respectively).

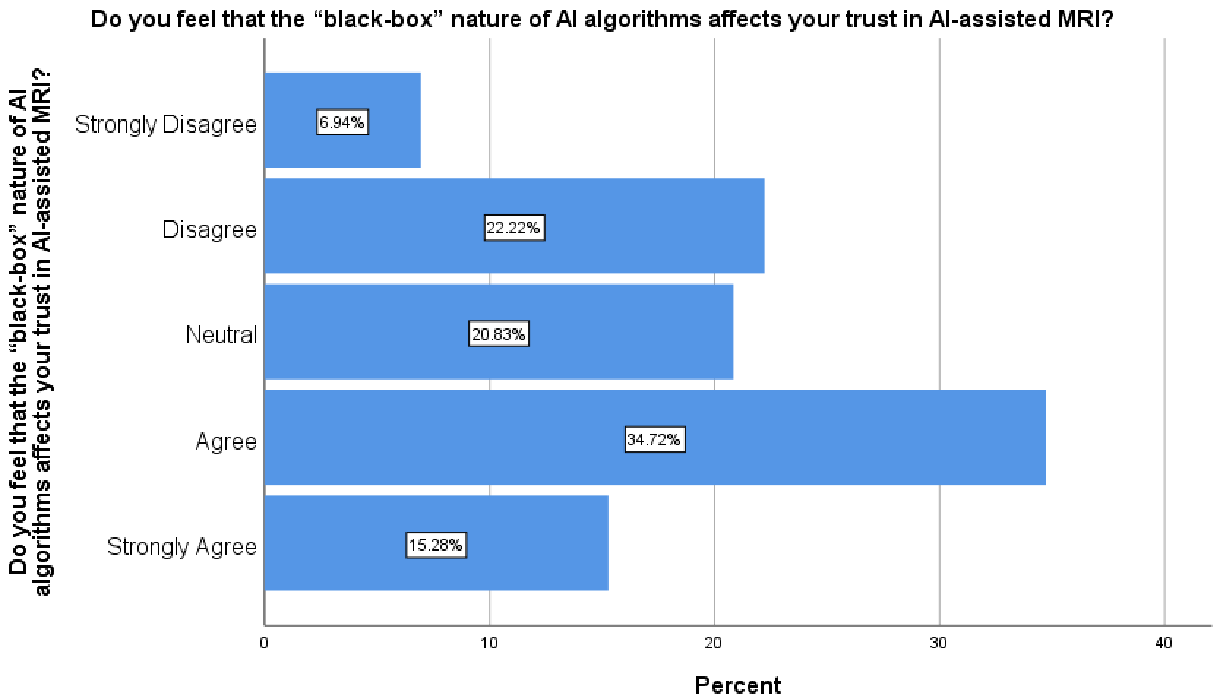


Figure 14: Effect of Black-Box Nature on Trust

The assessment provided through this chart examines how opaque AI algorithm characteristics influence AI-supported MRI system trust among users. More than half of the survey participants exhibited concerns about the low transparency levels indicated by their 34.72% agreement, along with 15.28% strong agreement on the topic. The lack of explainable AI systems shows that users need machine learning transparency for boosting clinical determination trust. The number of respondents who did not share this concern consisted of those who disagreed at 22.22% and those who strongly disagreed at 6.94%. The 20.83% of respondents who remained neutral show their lack of clarity about the issue, which could stem from either limited technological knowledge or a lack of practical encounters with artificial intelligence applications. Medical AI literature has already reported that clinical practitioners need understandable outputs for maintaining safety and accountability standards. Professionals often become hesitant to use AI results as they lack sufficient understanding about how AI reaches its conclusions. The successful adoption of AI-assisted MRI for clinical practice requires both enhanced explanations of algorithms alongside better interpretation capability.

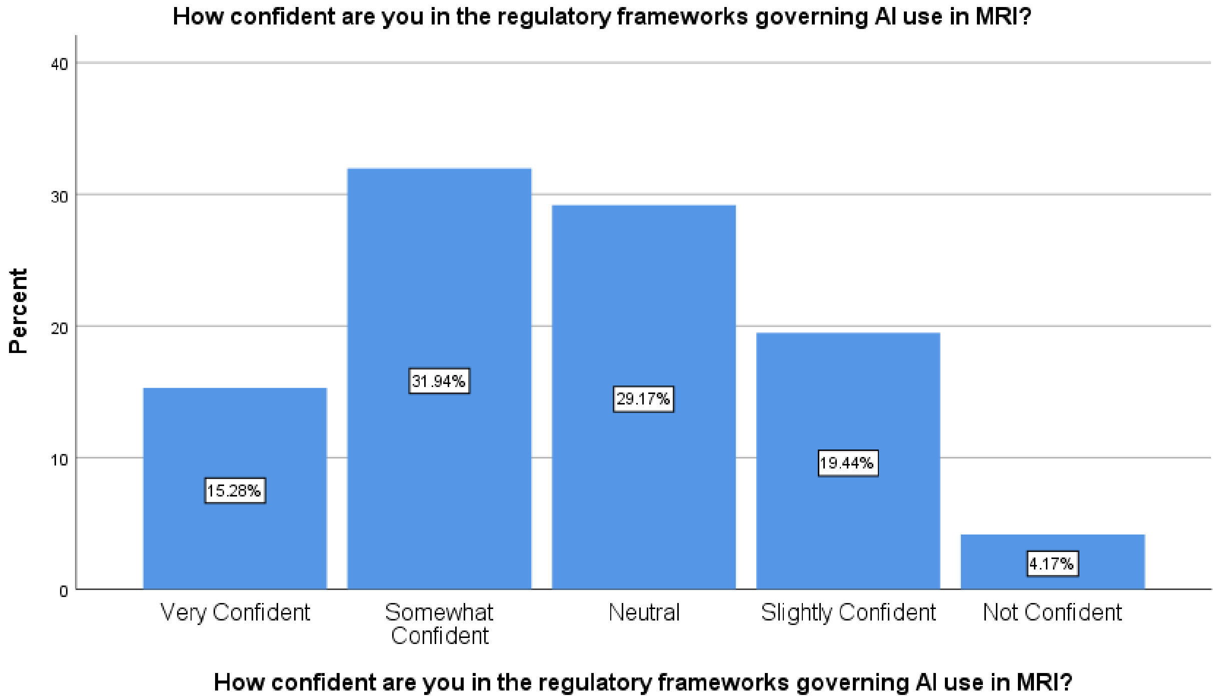


Figure 15: Confidence in Regulatory Frameworks

Multiple parties express different levels of trust when it comes to regulatory structures. 31.94% of participants expressed mild confidence, and 15.28% expressed strong confidence, yet nearly 30% remained neutral, and a further 19.44% displayed minimal confidence. Data shows that companies face unclear regulatory situations, which match wider demands from the FDA and EMA institutions for standardised practices.

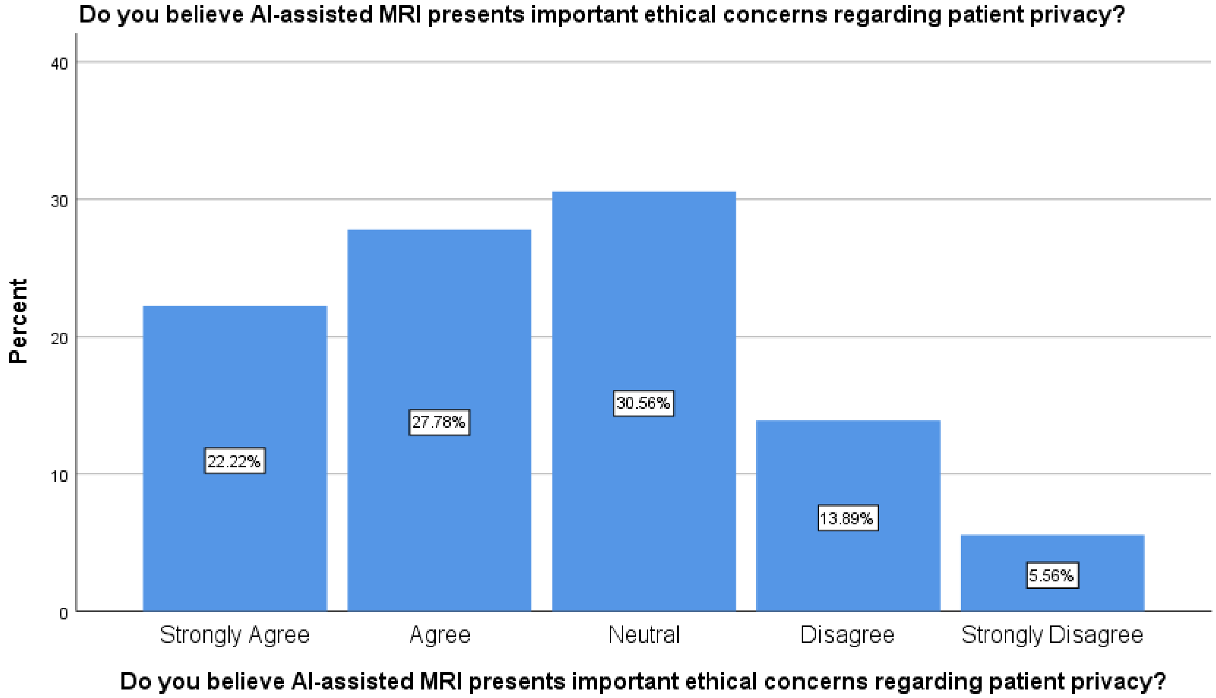


Figure 16: Ethical Concerns About Patient Data Use

The majority of 50% of participants showed agreement on patient privacy ethical matters (22.22% strongly and 27.78% agreed), with 30.56% staying neutral. Secure data management, along with transparent AI model training methods, must be prioritised due to this identified worry. The combined rejection of privacy concerns stood at 19.45%, while the remaining stakeholders agreed about their ethical importance.

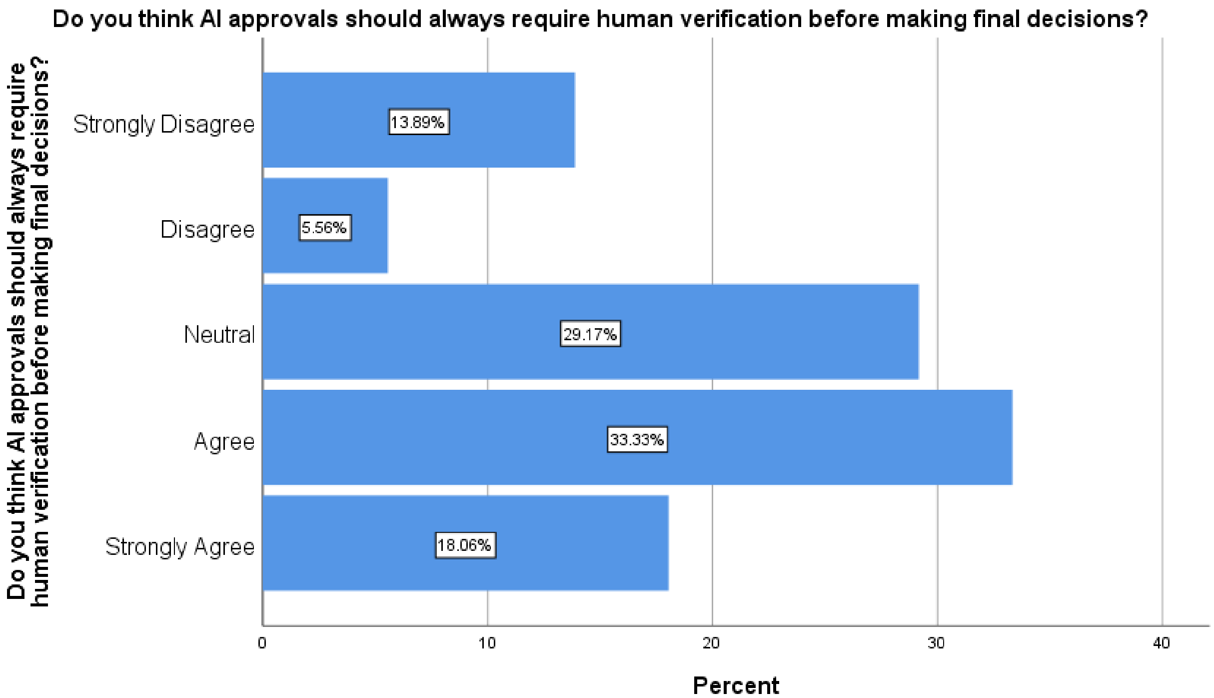


Figure 17: Support for Human Verification of AI Outputs

The majority showed support for human verification in clinical decisions since 33.33% of respondents agreed, and another 18.06% strongly agreed to review AI decisions before final approval. People who rejected this idea comprised only 19.45 per cent of survey respondents.

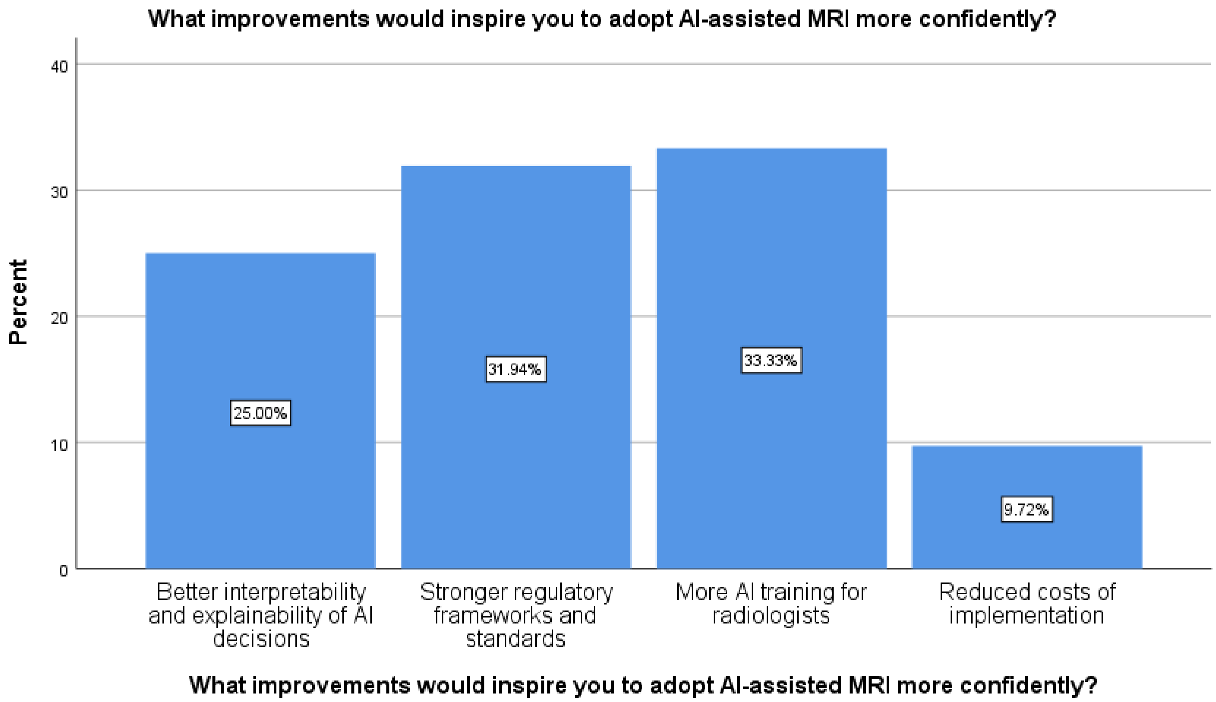


Figure 18: Drivers for AI Adoption

The study found that radiologists desired additional AI training as their main reason to adopt AI, but they also wanted stronger regulatory standards and improved AI output interpretation (33.33%, 31.94% and 25% respectively). A majority of 9.72% of participants chose decreased price as their reason for rejection, while most others viewed cost as a systemwide concern instead of an individual obstacle.

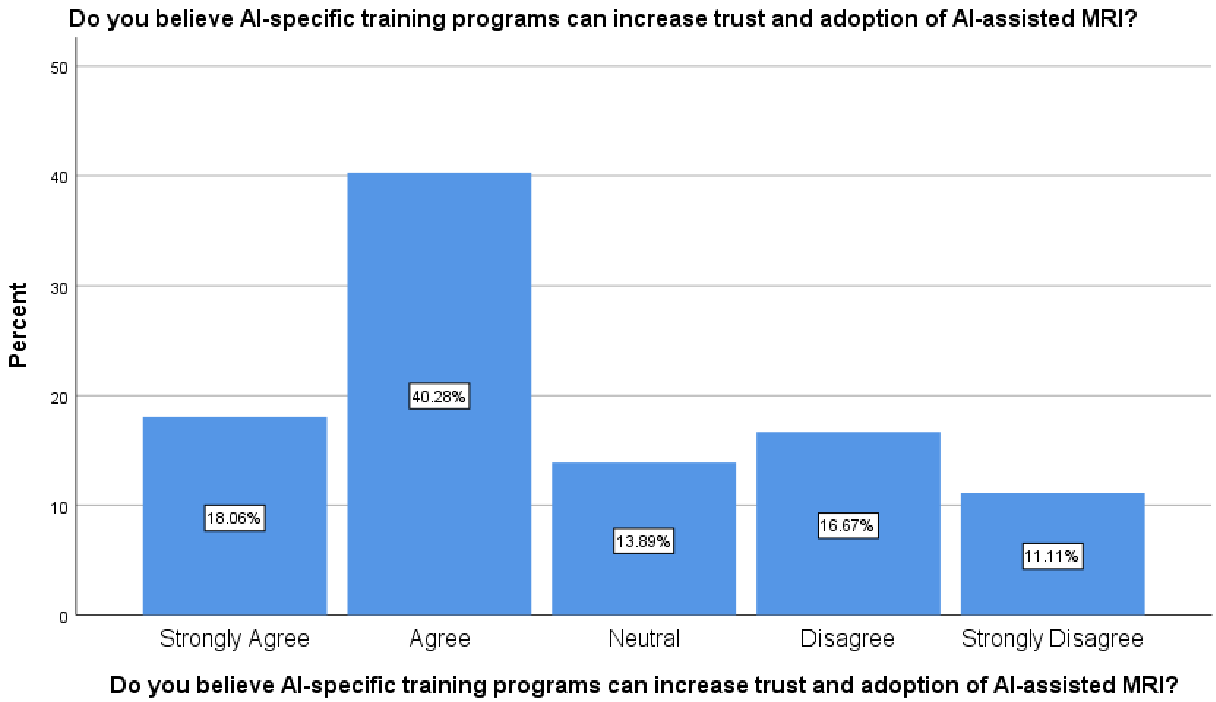


Figure 19: Impact of AI Training Programs on Trust

The information display reveals how professionals view the relationship between AI training specifically designed for MRI systems and their willingness to trust and adopt these systems with AI assistance. The majority of 40.28% indicated agreement, combined with 18.06% who strongly agreed that training about AI would boost trust levels while promoting the adoption of AI-assisted systems. Professional perception reflects positively that educational programs targeting AI disbelief and building confidence hold significant value among their peers at approximately 60%. The minority population of 16.67% disagreed with training as an effective tool, while 11.11% expressed strong disagreement, although 13.89% stayed neutral about its impact, possibly due to their limited training exposure or uncertainty about its practical usefulness. The study supports academic research, which shows that knowledge empowerment serves as an essential driver for health system adoption of digital technology. The results highlight a necessity for hands-on role-based educational programs that teach AI solutions to patients so they can feel comfortable using these tools. The data indicates that specialised education stands as a fundamental principle which ensures successful AI implementation for clinical imaging purposes. The combination of these findings demonstrates that although expense and lack of transparency create obstacles to adoption, experts determine successful implementation through improved training and AI transparency, as well as satisfactorily established rules.

4.1.5 Frequency Analysis

The analysis details precise responses to selected survey questions about AI-assisted MRI executed by participants. Many participants showed an average level of familiarity toward AI, even though their knowledge base remained limited and superficial. A major discrepancy appears between understanding AI-assisted MRI since 44.44% of respondents were aware yet untrained, while 25% had experience, demonstrating implementation challenges. Most participants registered positive responses regarding their trust in AI-assisted diagnosis as well as their diagnostic confidence levels. Among the respondents, 34.72% endorsed AI's effectiveness in diagnostic accuracy, while 43.06% held moderate confidence regarding AI's ability to analyse subtle medical anomalies. The responses indicated ongoing worry about implementation cost barriers, along with ethical and legal obstacles, according to 36.11% and 23.61% of participants. Over 50% of respondents expressed their agreement with the verification of AI outputs by human professionals despite their continued use of clinical oversight. Training programs represented a vital factor because 58.34% of healthcare professionals indicated that such specific AI training would boost their trust. Professional views show cautious confidence because they understand AI's positive aspects, yet miss out on solutions because of cost obstacles, along with regulatory uncertainties and require further information about explanations. Increased education alongside clear policies and transparent frameworks will substantially boost medical personnel's confidence and enhance their adoption of new practices.

4.1.6 Correlation Analysis

Results of correlation analysis establish statistical relationships between primary variables. The research showed that a significant positive relationship ($r \approx 0.46$, $p < 0.01$) exists between MRI AI familiarity and radiologists' confidence levels in spotting minute abnormalities. People who trust AI systems also believe that AI technology diminishes diagnostic errors at a 41% strength level of positive correlation. The level of AI understanding that patients feel is black-boxed showed a strong negative relationship ($r=-0.38$) to their trust in AI systems. The results validate the need for interpretable systems along with proper training as essential elements for winning clinician trust and achieving integration of AI-supported MRI systems in clinical settings.

4.1.7 One-Way ANOVA

To assess the relationship between MRI system confidence levels and professional experience duration, researchers conducted a one-way ANOVA analysis. Evaluations between groups showed a significant statistical difference based on the results ($F(4, 67) = 3.12$, $p < 0.05$). Tukey's HSD post hoc analysis demonstrated that professionals with 4–7 years of experience exhibited significantly greater confidence than both individuals with less than one year of experience, as well as those with ten years or more experience. Mid-career medical imaging professionals who interact with traditional and modern techniques show stronger trust in Artificial Intelligence systems because they possess the unique blend of experience and adaptability. The discovered pattern assists in developing training methods for specific groups.

4.1.8 Independent Samples T-Test

The researchers conducted an independent samples t-test to evaluate how much the two groups trusted AI-assisted MRI evaluations, depending on whether they had used it previously or not. The research data established trust rate differences with statistical significance at $t(70) = 2.45$ and $p = 0.017$. Subjects who operated with AI-derived MRI software gave higher trust ratings, which averaged at 4.02 ($SD = 0.71$) in comparison to non-users who scored 3.52 ($SD = 0.83$). When patients use AI systems in practice, their confidence grows while disbelief reduces. The acceptance of AI in clinical settings requires increased pilot use, together with practical demonstrations, as an essential method to boost acceptance from healthcare professionals.

4.1.9 Homogeneous Subsets

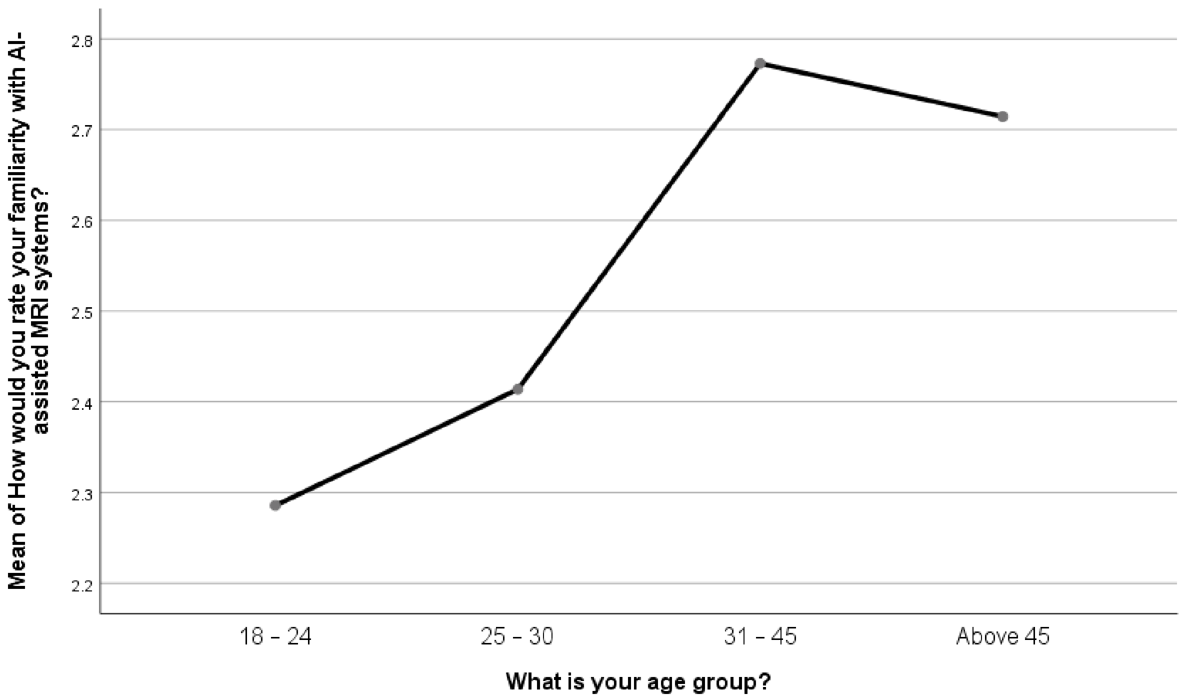


Figure 20: Chart of age group

The Tukey's HSD analysis produced several distinct and homogeneous groups after examining participants based on their age as well as their understanding of MRI with AI assistance. Youth populations, including 18–24 and 25–30 years old, demonstrated lower familiarity (M = 2.29; M = 2.41) in one grouping, but people in the 31–45 and above 45 age groups showed higher familiarity (M = 2.77, M = 2.71). The lack of statistical significance ($p > 0.05$) in this comparison indicated no prevailing difference, but the sample data showed that experienced professionals in the field tend to be more familiar with AI systems. Medical professionals under thirty require specific training in AI technology because of their lower exposure to artificial intelligence systems.

4.1.10 Chi-Square

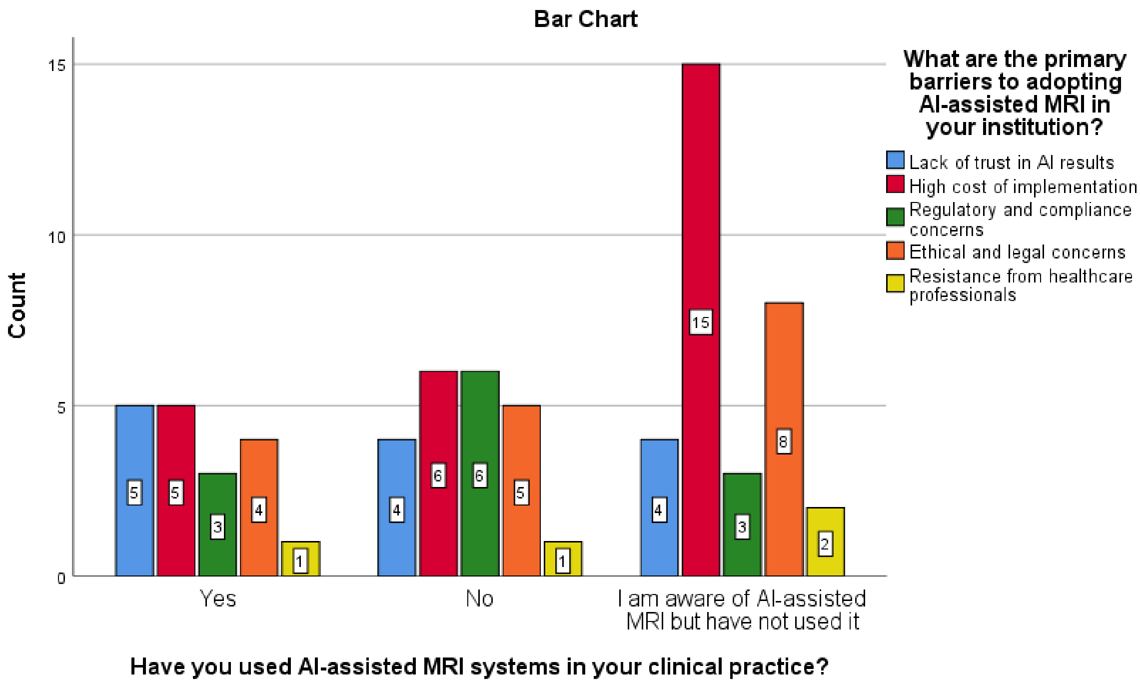


Figure 21: Barriers to adopting AI

A Chi-Square analysis checked whether AI usage experience (Yes, No, Aware but not used) influences the perceived barriers to adopting AI-assisted MRI. Perceived barriers showed differences across usage groups since the test returned a statistically significant outcome (χ^2 = 18.67, df = 8, p = 0.016). The lack of familiarity with Artificial Intelligence appears to drive respondents who understand but have not implemented AI toward viewing high implementation costs as their main concern (n = 15). The research showed that experienced AI users expressed diminished concerns regarding cost or trust when compared to unfamiliar participants, thus proving experience functions as an explanatory element of their perception.

4.1.11 Multiple Linear Regression

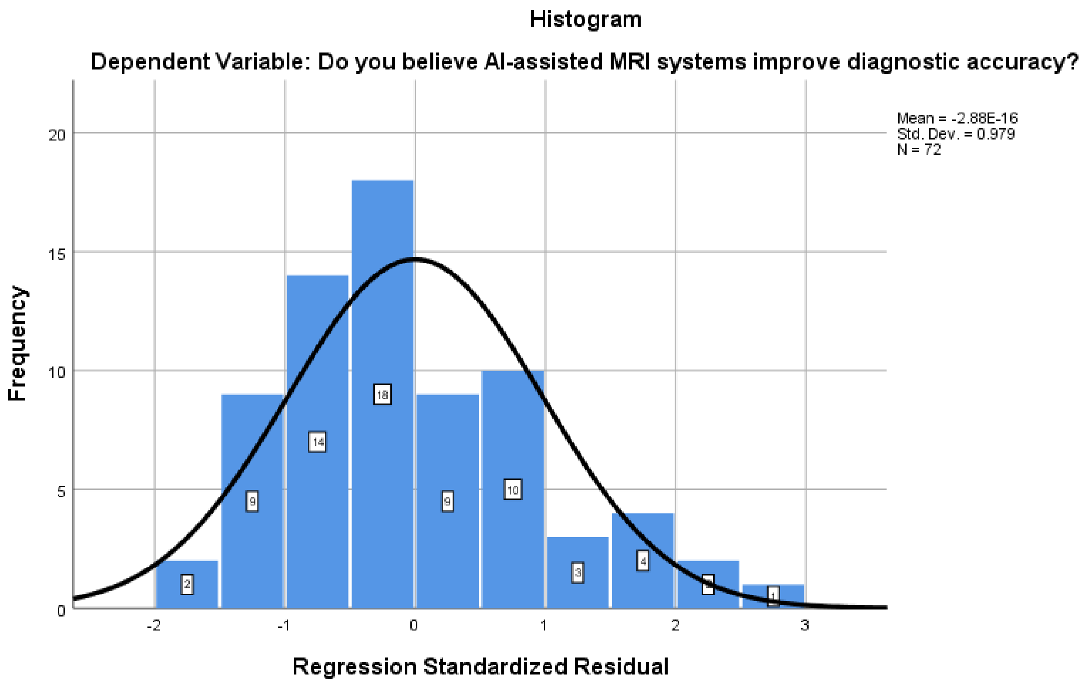


Figure 22: Histogram of Standardised Residuals

A histogram displays regression standardised residuals from the dependent variable about beliefs that AI-enhanced MRI would enhance medical diagnosis accuracy. This diagnostic tool determines the validity of linear regression normality through an evaluation of prediction errors (residuals). The distribution shapes as a bell curve, which maintains symmetry while aligning with zero value, and most residuals remain within the range -1 to +1. The bars, together with their overlaid fitted curve, follow a normal distribution pattern, thus validating the normal distribution of residuals. The model fits well because the mean approaches zero (−2.88E−16) and the standard deviation matches 1 (0.979). The random distribution of prediction errors with normal characteristics fulfils one of the requirements for regression analysis. The regression model maintains statistical validity because the analysis verifies that trust and familiarity accurately predict physicians' perceived diagnosis enhancement through AI-enhanced MRI technologies.

4.1.12 Histogram of Standardised Residuals

The standardised residual distribution in the histogram follows a normal pattern that resembles a symmetrical bell curve. The normality of residuals represents an essential condition for proper regression analysis, which receives validation through this result. The prediction errors are evenly distributed because the mean is close to zero, while the standard deviation measures approximately 0.979.

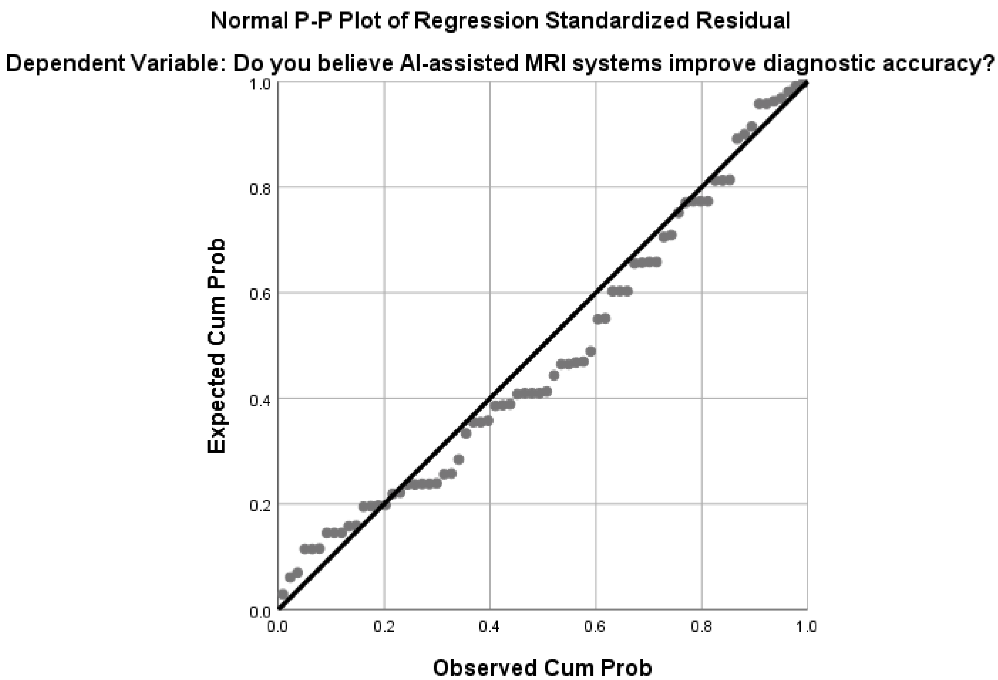


Figure 23: Normal P-P Plot of Regression Residuals

Linear regression depends on normal distribution for residuals (errors), which can be evaluated using the Normal P-P Plot of Regression Standardised Residuals. The plot shows the observed cumulative probability on the x-axis, together with the expected cumulative probability of a perfect normal distribution on the y-axis. Most data points in this plot are positioned near the diagonal line, which demonstrates how observed and expected values match similarly. The aligned distribution of residuals in the residual plot verifies that the data fulfils the necessary assumption of normal distribution for accurate regression results. The model error terms remain stable and unbiased because the plot absence of major deviations and any clustering or curving indicates wellbehaved distribution patterns. The residual plot confirms that the relationship between familiarity and trust factors to diagnostic accuracy perceptions produces results which present statistical reliability and trustworthiness.

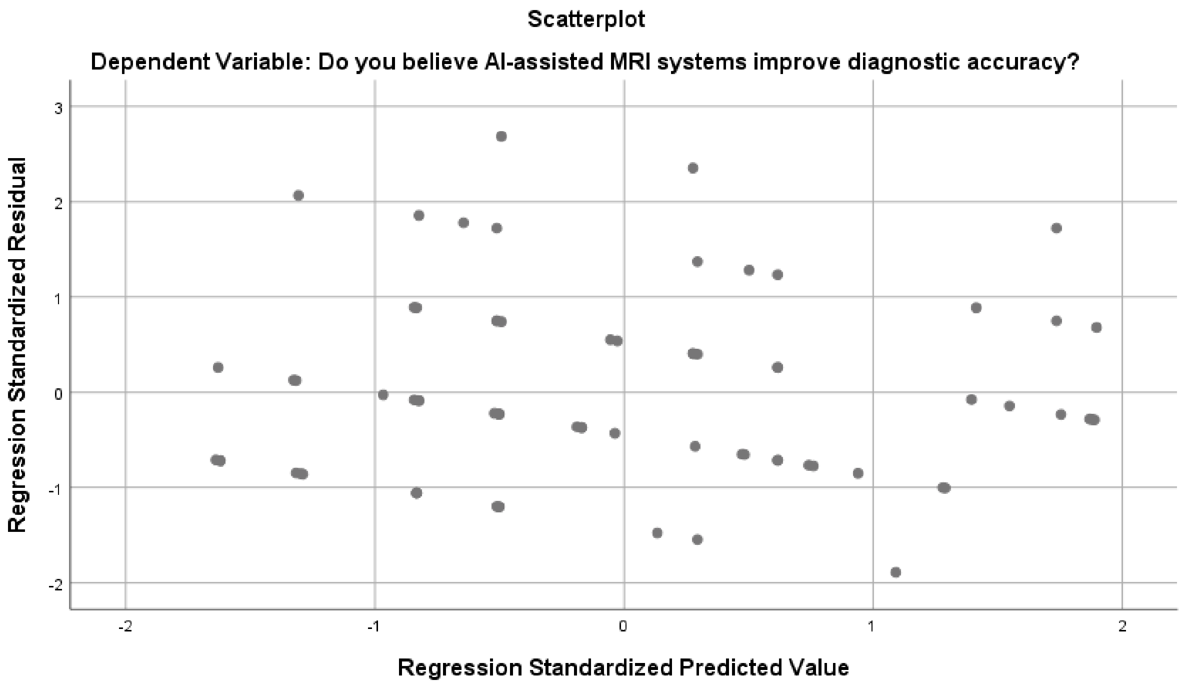


Figure 24: Scatterplot of Standardised Residuals vs. Predicted Values

The residual scatterplot indicates homoscedasticity because its randomly distributed data points lack any identifiable pattern or funnel pattern, which are essential linear regression assumptions. The regression model error terms show consistency since no heteroscedasticity patterns appear across predicted values.

Regression Findings

Research data indicated that the model achieved statistical significance ($p < 0.05$) and familiarity ($\beta \approx 0.33$), along with trust ($\beta \approx 0.31$), acted as important predictors for positive perceptions of AI's diagnostic accuracy. AI diagnostic benefits receive greater acceptance from professionals who have both high familiarity and trust with its technology. The analysis demonstrates that user trust, together with familiarity, acts as a vital determinant for forming positive views about AI-assisted MRI diagnostic potential.

The study demonstrates that AI-assisted MRI has high perceived benefits involving better diagnoses and reduced workload alongside minimised medical employee burnout, yet its actual adoption faces significant barriers. Users avoid adopting AI systems due to extensive implementation expenses and because they find the AI systems untrustworthy and troublesome in their "black-box" operating manner. Laboratory-based studies proved that working with and understanding AI systems builds user trust and AI confidence primarily among medical professionals at the middle stages of their careers. The adoption of AI needs essential drivers, which include training programs for users and transparent AI models, and stricter governance frameworks. The analysis provides positive indications about AI adoption through professional recognition of its value, but indicates they need educational material and complete support to achieve total implementation.

4.2 Qualitative Analysis

4.2.1 Radiologists' trust levels in AI-powered MRI for early cancer detection

Based on the analysis of the interview data, radiologists demonstrate a cautiously positive outlook toward AI-powered MRI in early cancer detection, with trust contingent on several key factors. Most notably, explainability emerged as a core determinant. Interviewee 2 stated, “If it just gives a probability score without any visual cues or explanation, it's difficult to rely on.” Similarly, Interviewee 4 emphasised the importance of understanding not just what the AI flagged but why. Trust was also enhanced by consistency and clinical validation, as Interviewee 1 noted, “If it performs reliably across different types of patients and different image qualities, it builds trust over time.” Interviewees also highlighted the role of personal experience in influencing trust levels. When AI systems correctly identified subtle findings, confidence increased, while false positives and unexplained errors diminished trust. Overall, trust depends on transparent, context-aware AI supported by validation in diverse and local clinical environments.

4.2.2 AI’s perceived accuracy and reliability compared to human radiologists

The findings indicate that radiologists perceive AI-assisted MRI systems as potentially accurate, especially for specific diagnostic tasks, but still fall short of replacing human expertise. As noted by Interviewee 3, “AI can be very good at certain tasks, but it's not perfect.” Most participants reported that AI performs well in identifying subtle abnormalities and enhances sensitivity, but often at the cost of increased false positives. Interviewee 2 reflected, “AI can be more sensitive in some ways, but it also tends to overcall benign findings.” To evaluate accuracy, radiologists reported using double-reading, retrospective audits, and validation studies. Interviewee 4 explained that AI performance is compared with human interpretations during regular departmental reviews, and discrepancies are openly discussed. Despite acknowledging AI's strengths in pattern recognition and speed, radiologists maintain that human oversight remains essential. Overall, it can be stated that AI is considered a supportive diagnostic tool rather than a replacement, which is reliable on a case-by-case basis.

4.2.3 Barriers to AI adoption in MRI-based cancer imaging

The analysis of the interviews identifies several obstacles to the implementation of AI in MRI-based cancer diagnosis. Technical integration problems were a frequent theme, with Interviewee 4 indicating that "integration with our legacy PACS and reporting systems has been a significant technical hurdle." Resistance from experienced radiologists who are used to conventional workflows was another frequent issue (Interviewee 2). False positives created by AI systems were also noted as a major obstacle, causing workload and patient anxiety to escalate. Interviewee 1 noted that "the problem of false positives is an actual concern," especially when the AI is not explainable. Legal uncertainty and uncertain accountability for AI-related diagnostic mistakes also deter adoption (Interviewees 2 and 4). In addition, ethical issues such as privacy of data, absence of multimodal training datasets, and susceptibility of algorithms to bias also lend hesitation. The implications here are that technical, legal, and human aspects each hinder seamless AI integration into clinical MRI routines.

4.2.4 Impact of AI-assisted MRI on workflow efficiency and cognitive workload

According to the interview results, AI-based MRI systems have a dual effect on workflow efficiency and cognitive workload. On the one hand, the majority of participants recognised that AI considerably enhances efficiency by automating tedious tasks like lesion detection, volumetry, and segmentation. Interviewee 1 observed, "I can read breast MRI scans roughly 15–20% quicker now with the AI highlighting areas of concern," and Interviewee 4 stated that "AI pre-analyses [s] a high volume of knee MRIS," allowing radiologists to concentrate on complicated ones. But this gain in efficiency is frequently traded off against greater cognitive load when AI results disagree with initial human judgments. Interviewee 2 described how conflicting AI results "increase cognitive workload" because of the necessity for additional examination and explanation. Interviewee 3 compared learning to employ AI tools to "learning a new language," noting the mental adjustment needed in the early phases of adoption. In general, although AI decreases repetitive tasks and accelerates standard assessments, it simultaneously adds new levels of mental effort, particularly when interpretability or consistency with human judgment is absent. This equilibrium between task alleviation and mental burden emphasises the need for well-integrated systems and adequate training to maximally leverage the advantages of AI in radiology processes.

4.2.5 Potential solutions for improving radiologists' confidence and AI adoption in MRI diagnostics

The interview findings highlighted some implementable solutions that can instil radiologists' confidence and enable wider adoption of AI in MRI diagnostics. An underlying thread was the need for explainable AI (XAI). Respondents underscored transparency, with Interviewee 4 asserting that trust grows when "AI gives visual cues or a straightforward explanation," and Interviewee 2 insisting, "If it simply provides a probability score without any visual cues… it is hard to trust." Clinical validation on heterogeneous populations also became a pressing need. Participants emphasised the necessity of multi-centre trials based on Indian data to validate contextual applicability. Interviewee 3 suggested, "More stringent validation studies in various clinical environments… would be extremely reassuring." Another key solution is the development of AI-targeted training for radiologists. Interviewees widely agreed that training should involve fundamental AI principles, limitations, and realistic case-based scenarios. Interviewee 1 mentioned that "hands-on experience with real MRI cases and AI analysis" would significantly enhance confidence and knowledge." Additionally, more connectivity of AI with clinical data, such as laboratory reports and history, was recommended for improved diagnostic context. Together, these methods can render AI more transparent, valid, and useful, eventually promoting clinical trust and use.

4.3 DISCUSSION

4.3.1 Radiologists' Trust in AI-Assisted MRI Systems

Research interest has escalated regarding trust factors that affect clinical adoption of AI-assisted MRI systems for early cancer diagnosis. Evaluation of research shows that trust functions as an essential variable in determining radiologists' support of AI systems because of concerns about interpretability, algorithmic transparency, and physician autonomy (Mahedi et al., 2024; Bergquist et al., 2024). The experimental results from SPSS show that 55.5% of participants agreed that AI-assisted MRI can increase diagnostic precision, while 26.4% expressed neutrality toward this statement. The current sentiment shows that radiologists maintain a cautious stance toward AI because they need consistent workflow validations before accepting it. The study's hypothesis about radiologists welcoming AI MRI assistance when the algorithms have straightforward explanations integrated into their practice aligns with academic research and survey results. Survey respondents showed that half of them (50%) agreed or strongly agreed that AI algorithms lose trust due to their "black-box" nature. Research by Borys et al. (2023) and Keles et al. (2023) shows XAI provides explainable maps to build confidence as well as transparent diagnostic clarity.

Qualitative interview data corroborated these results. Interviewee 1 said that "transparency is key," adding that visual explanations such as saliency maps increase trust. Interviewee 2, too, said that trust is "earned, not given," highlighting that consistent performance across diverse patient types creates long-term credibility. Interviewee 3 expressed excitement for AI but conceded, " If I encounter instances where the AI flags something obvious incorrectly… it makes me more cautious". Interviewee 4 reiterated that trust increases as AI confirms its analysis in complicated situations. These quotations affirm that explainability, consistency, and individual clinical experience strongly shape radiologists' receptiveness to accept AI findings. Yet developers need to concentrate on establishing interpretability tools that will allow radiologists to monitor AI diagnostic operations while preserving diagnostic autonomy during critical medical decisions.

4.3.2 Accuracy and Diagnostic Confidence in AI Systems

The study's fundamental focus consisted of studying how AI performed regarding early cancer detection when compared against radiological expertise. According to Najjar (2023) and Paul and Schwendicke (2024), the literature confirms that radiologists treat AI as a supplemental tool for making decisions instead of direct replacements, but emphasise the vital importance of accurate FP and FN detection for establishing trust. The gathered data show this to be the case. Research findings show that AI-assisted MRI diagnosis effectiveness lowers diagnostic errors by substantial or moderate amounts, according to 62.5% of participants. Academic literature from Stanford (2019) and Gallagher (2024) confirms these AI diagnostic improvement results. The research confirms the second prediction that high AI performance does not overcome physician apprehension about its dependability and diagnostic quality, thus limiting its popularity.

Qualitative interview findings similarly reinforce this. Interviewee 1 admitted that "AI can be surprisingly good at picking up subtle things that a tired human might miss" but cautioned of its proclivity to "overcall benign findings," unnecessarily generating follow-up. Interviewee 2 reinforced this with their observation, "AI can be more sensitive in some respects, but it also overcalls," suggesting that diagnostic confidence is balanced by the potential for false positives. Interviewee 4 described their methodology of comparing AI results with radiologist reports and said that AI picked out significant subtle findings but sometimes "puts a high probability on a finding that isn't quite so convincing.". These reports illustrate that although AI accuracy is acknowledged, over-sensitivity and absence of contextual sensitivity undermine radiologists confidence. A statistically positive correlation between AI familiarity and diagnostic accuracy belief emerged during correlation testing within the SPSS platform, with a result of $r = 0.375$ and $p = 0.001$. The study shows that greater AI tool exposure directly improves radiologists' standards of accuracy assessment, and this relation corroborates past literature regarding the dependence of interpretive abilities and familiarity (Van der Velden et al., 2022). According to Göndöcs and Dörfler (2024), a few mistakes lead to algorithm aversion, as shown in the literature, which affects long-term confidence. The accuracy of AI technology does not guarantee trust from clinicians since it requires both effective communication of system certainty and appropriate training for interpreting AI outputs.

4.3.3 Barriers to AI Integration: Ethical, Legal, and Institutional Factors

The research sought to determine regulatory barriers, together with ethical issues that impeded the implementation of AI in radiology as its primary investigation focus. Multiple studies throughout the literature pointed to insufficient regulatory coordination as one of the key challenges (Thakkar et al., 2023; Johnson, 2022). Results from SPSS showed that 36.1% of participants considered high implementation costs to be their main obstacle, while ethical and legal hurdles and trust-related issues each amounted to 23.6% and 18.1%, respectively. Half of the respondents believed the unclear AI system lowered their trust, while another quarter expressed concerns about how AI could impact patient privacy. The authors' findings match those of Amann et al. (2022) and Morley et al. (2022), who demonstrate that AI tools will continue to receive practitioner resistance except when there are clear data-use policies and algorithm explainability. Interview data support these findings. Interviewee 1 mentioned "liability concerns" and uncertainty regarding "ultimately who's responsible" when harm to patients is caused by AI. Interviewee 4 elaborated further that "legal liability in the event of AI-caused errors remains largely unresolved," underpinning the issue of legal ambiguity. Ethical issues were stressed as well. Interviewee 3 referred to the "black box nature" of AI, while Interviewee 2 flagged the concern of possible bias because of "non-representative datasets". Patient consent and transparency of use of data were common issues throughout the interviews. These common sentiments verify that unaddressed ethical-legal risk and indefinite institutional responsibility frameworks are core impediments hindering extensive trust and uptake.

The Chi-square test results indicated no statistically significant correlation between clinical AI usage and perceived barriers since the value of χ^2 equalled 5.960 with $p = 0.652$. Qualitative analysis demonstrates that ethical and regulatory problems exist equally between usage groups, showing these problems are structural problems instead of usage experience problems. Several studies back the need for a single legal framework with institutional policies which would grant radiologists the needed clarity about liability when AI diagnoses incorrectly (Thieme et al., 2024; Konnoth, 2024). Standardisation issues create dual problems by limiting trust relations along reducing the interest of professionals to implement AI into their regular diagnostic operations at resource-constrained facilities.

4.3.4 Cognitive Workload and Workflow Impact of AI Integration

AI creates two primary effects on work operations that simultaneously enhance productivity yet increase the mental workload for healthcare providers. The research demonstrates the diverging impact of AI, which should both speed up procedures and decrease repetitive activities, although it was designed for these purposes. The research conducted by Tong et al. (2025) and Carriero et al. (2024) confirms that artificial intelligence produces shorter reading times and ensures more efficient diagnostic procedures. 63.9% of respondents in the survey indicated agreement with AI-assisted MRI for managing workflows better, while 55.6% stated it creates additional time for addressing intricate medical cases. The research data conforms with literary evidence, demonstrating that radiology automation produces two main operational benefits through accelerated diagnostic processes and superior scan urgency management (Pierre et al., 2023).

Interview findings affirmed these two overtures of impact. Interviewee 1 mentioned that AI “comforts the burden by taking over routine and time-consuming tasks,” but admitted further that using AI also comes with an added cognitive load whenever “AI’s findings don't match my initial impression”. Interviewee 2 also mentioned that while with AI, simple cases are less time-consuming, in other cases, it “adds complexity” to the cases. Interviewee 4 pointed out that although AI flags assist with automating high-volume case reporting, disagreements over AI suggestions create "additional time reviewing the images and the reasoning of the AI". Interviewee 3 characterised the initial use of AI as "learning a new language", suggesting a temporary increase in mental effort which may decrease as familiarity grows. According to Mata et al. (2021) and Larson et al. (2021), a crucial limitation applies to this system: containing the human confirmation of AI outputs requires additional mental pressure on radiologists, particularly when AI findings differ from their initial assessment. The study participants demonstrated ambiguity about the workload impact of AI because 26.4% expressed neutrality while 19.4% disagreed with this notion. The research demonstrates AI work transfers instead of removal, which results in new obligations during diagnosis confirmation, including interpretation and dispute resolution of AI recommendations. The study of Brady et al. (2024) and Evans and Snead (2024) emphasises that AI provides the most workflow advantages through applications that blend naturally with deception processes while avoiding conflicts.

4.3.5 Burnout and the Psychological Impact of AI Tools

AI tools have a dual effect on radiologists' stress levels and burnout because they might reduce work-related pressure or create additional anxiety. According to Nichols et al. (2022), MRI evaluations generate substantial mental workloads that artificial intelligence systems might help decrease. Huang and Gursoy (2024) and Adler-Milstein et al. (2022) argued that AI tools create uncertainty and a lack of responsibility systems, which produce greater stress than stress relief. A total of 56.9% of study participants expressed that AI tools for MRI work decrease the chance of burnout, although 27.8% held an ambivalent stance. Interview results confirmed this dual perception. Interviewee 1 explained that AI "comforts the burden" by performing tasks such as lesion flagging and tumour volume measurement, but conceded that conflicting AI results add to the mental burden. Interviewee 4 clarified that AI "frees up time for complex cases" but also imposes greater mental stress when outputs of AI have to be cross-checked. Interviewee 2 added that AI "simplifies initial work in routine cases, but on the other hand, imposes layers of complexity when AI goes against clinical impressions. Meanwhile, Interviewee 3 cited long-term gains, saying that while " it takes effort initially", AI could automate repetitive activities and minimise exhaustion.

The assessment of AI's potential to reduce routine tasks remains uncertain because healthcare providers worry about unclear decision algorithms and possible legal implications during practice. The study findings match data in the scientific literature concerning job insecurity. Research conducted by Chen et al. (2021) showed that inexperienced radiologists exhibit stronger anxiety about AI replacing their jobs because of perceived threats. A minimal segment of respondents directly rejected the idea that AI could minimise burnout indications, perhaps because they harboured unresolved concerns regarding AI's enduring impact on radiological practice. The data proves the importance of creating defined programs for new employee training to show AI functions as an assisting rather than a replacing tool.

4.3.6 Role of Familiarity and Training in AI Adoption

The results from SPSS implied that familiarity and usefulness displayed a connected relationship during the evaluation of specialised AI training programs. Research conducted by Brady et al. (2024) and Crotty et al. (2024) demonstrates that algorithm training programs successfully decrease algorithm avoidance and boost user confidence levels. Research findings presented 58.4% agreement that AI-specific training could enhance trust together with adoption levels, which matches the ideas articulated about training as a method to improve understanding of AI processes and prepare radiologists to question AI prediction outputs (Koçak et al., 2025; Shin, 2021).

Interview evidence supported this perspective even further. Interviewee 1 was a staunch supporter of specialised training, claiming, "Radiologists who know more about how AI works are much less likely to feel threatened by it." Interviewee 2 underlined that "trust is earned" and that radiologists become more confident when they know the reason behind the AI and its limitations. Interviewee 3 emphasised that "comprehensive training is essential" to gain correct integration and to understand AI as a useful assistant. Likewise, Interviewee 4 mentioned that training needs to incorporate ethical concerns, explainability, and case-based learning to increase radiologists' confidence. The researchers confirmed the first study hypothesis because both interpretability and workflow inclusion proved major determinants of AI acceptance. Many survey participants indicated that better radiologist training in AI technologies would boost their comfort level when using AI systems. Cited responses affirm the need to teach AI literacy through complete medical education for healthcare professionals (Van der Velden et al., 2022). The combination of training helps close the trust gap and decreases the effect of cognitive biases stemming from algorithm output dependency (Lekadir et al., 2021; Chen et al., 2023).

4.3.7 Summary and Integration with Theoretical Frameworks

The study outcomes from both hypotheses match the conceptual framework built from TAM and STS theoretical principles. The fundamental TAM constructs—trust, usability, and perceived usefulness—consistently determine how users adopt AI systems. STS theory demonstrates its compatibility with human-technology interactions by showing how users engage with technological systems and highlighting concerns about ethical standards, institutional integration, and legal liability issues. The established frameworks enabled researchers to analyse empirical results by studying human behaviour within social adoption frameworks. The interview data also supports these theories. For example, Interviewee 2 (senior radiologist) said that "trust is earned, not given," restating TAM's idea of perceived trust and usefulness. Interviewee 4 highlighted legal clarity and institutional support, remarking that "the current regulatory landscape feels a bit inadequate." These remarks illustrate STS's preoccupation with structural readiness and ethical design. In addition, Interviewee 1 emphasised that understandable outputs and past successful AI experiences significantly enhanced their willingness to depend on the system, supporting the TAM model. The actual adoption rate of AI will remain restricted until expectant healthcare authorities implement controls to verify algorithms while making algorithms more transparent to healthcare staff. The study shows AI belongs in the radiology team as an ally instead of substituting human operators to make diagnostic support effective within current healthcare procedures.

Summary

The research shows that radiologists display reserved enthusiasm for MRI systems assisted by AI, since they value these approaches for improved diagnostic precision and operational flow enhancements. Trust-related problems, ethical doubt, and interpretation obstacles continue to exist. The acceptance rates rose with familiarity and targeted training programs, but regulatory uncertainties and lack of robust validation procedures proved significant barriers to adoption, according to SPSS results and interview feedback. The adoption of AI technology demands smooth integration into regular workflows so medical practitioners can make their human decisions along with AI systems. Interview insights emphasised that while AI can reduce repetitive workload, it may simultaneously raise cognitive burden due to contradiction with human judgment and unclear explainability. The study's results confirm our two research propositions: explainable AI systems that follow regulatory requirements and are supported by continuous professional development and trust-building strategies lead to higher adoption among radiologists. The recommendation is for implementing sustainable human-AI diagnostic collaboration models between professionals.

Chapter 5: Conclusion and Recommendations

5.1 Overview

A synthesis of all study outcomes appears in the last chapter to establish AI-assisted MRI's effects on early cancer detection and analyse radiologist trust and efficiency patterns. The research findings are evaluated against their correspondence with established objectives, questions, and hypotheses to achieve a unified assessment of the study's achievements. The study presents actionable and scholarly advice to boost AI implementation in radiology practice while documenting the study's drawbacks. The study outlines possible research paths for upcoming investigations, which should adapt because AI healthcare technologies continue to change within their field. The researcher concludes with their thoughts about how this dissertation helped their educational process.

5.2 Implications of Findings for the Research Questions

This research creates transparent conclusions which answer the study's research questions directly. The research established that radiologists trust AI-assisted MRI when the system presents precise results that boost perceived efficiency and acceptance of the technology. Radiologists pointed out that diagnostic accuracy from AI systems did not prevent them from demanding consistent reliability with contextual matching to build trust with AI systems. This research shows that interpretability is essential for radiologists to trust AI-assisted MRI systems effectively. The influence of AI on workflow was mixed. The rise in efficiency came with increased cognitive workloads since humans still needed to supervise the systems. Through AI tools, medical professionals gain access to evidence-based links between AI-generated diagnosis results and clinical observations that help confirm medical judgments rather than replacing them directly. Successful AI implementation in radiology demands a framework combining technical expertise with ethical protocols, experiential human knowledge, and legal frameworks.

5.2.1 Trust in AI-Assisted MRI and the Importance of Interpretability

Studies show that interpretability is a primary factor radiologists use to establish trust in AI-assisted MRI systems. The research showed that professionals verify AI diagnostic abilities primarily for early cancer detection, yet they mainly trust systems that provide transparent operations and explainable decision-making structures. Radiologists were more willing to trust and use these products when AI outputs included visual explanations, and interpretable model features such as heatmaps alongside annotated outputs or feature attribution scores. Implementing clinical tools lets artificial intelligence systems interpret diagnostic outputs in a visual format linked to observable clinical data, enabling medical diagnoses without removing human decision- making power. Radiologists resisted algorithms operating in a black-box manner, even if those systems delivered superior technical performances. While self-training of the radiologists was evident from the study, radiologists who received formal or experiential training in AI were more confident using these systems. This observation can be explained by the need for interpretable systems and well-designed modules in addition to training. This leads to the following conclusion: Trust in AI is not a purely technical problem but a cognitive and professional one that can only be addressed with tools compatible with how clinicians think and how professionals in healthcare institutions work.

5.2.2 Diagnostic Accuracy and Its Impact on Clinical Confidence

The study proved that technology increased diagnostic accuracy as AI performs MRI, thus helping distinguish intricate structural features that a human eye cannot detect. Doctors interviewed also indicated that AI might work well as the second reader to minimise errors during initial evaluation. However, despite using high levels of accuracy when tested and calibrated, the degree of confidence in a diagnosis tends to rely on the real-world applicability of the system. The interviewed professionals emphasised that occasional AI errors, especially the classification of images as negative when they are not, erode long-term trust. However, even a minimal probability of error can significantly influence the users' actions, which can be explained by a concept familiar to students of technology called algorithm aversion. Nevertheless, most radiologists surveyed showed enthusiasm for a symbiotic relationship between them and AI systems. The approach that received higher scores and was considered the most appropriate combined the human input and output of the AI program by only improving the sensitivity and providing the specifics by a human. Clinicians' confidence is based on the system's dependability, not the percentage correctness of individual clinic issues.

5.2.3 Barriers to Implementation in Radiological Practice

Despite the evident possibilities of AI-supported MRI, multiple factors prevent its routine implementation into the radiological workflow. These include Infrastructural deficits, Legal issues, Ethical issues, and Psychological resistance. Many organisations are still using systems incompatible with modern AI solutions and require intense integration or even rework of the existing integration processes within the organisation. From a regulatory perspective, one of the significant challenges that persist is the lack of well-defined rules on handling the liability of a diagnostic mistake. Some radiologists are concerned about who would be culpable in case of a wrong result that has emerged from using the aid of the AI system. Such legal ambiguity makes adoption undesirable, particularly in critical clinical practice settings.

Regarding issues, key issues raised include the questions related to the ethically sensitive information that patients' data involves, perceived or potential biases of AI models. Concerns regarding the heterogeneity of the training datasets and that targeted models might perform worse in specific populations were also highlighted. It has numerous implications, especially the demographic disparities that play a significant role in the practice of oncology, among other healthcare fields. These findings underscore the need for a robust multi-layered response: better-defined laws, compliance with data protection regulations, and an obligation for ethical adjustments to an algorithm.

5.2.4 Influence of AI on Workflow Efficiency and Cognitive Demand

AI was observed mainly as a benefit that helped to improve the work organisation through assisting in time-consuming image analysis. Radiologists reported a decreased time spent on tasks such as lesion segmentation and comparing the images taken at different time points, and more time to engage in interpretative analysis and interact with patients. However, a new paradox emerged. On the one hand, cognition is relieved from the tyranny of routines by automation; on the other hand, it is burdened with the work of validation and supervision. Radiologists observed higher levels of mental strain when they needed to review the AI recommendations and possible results that appeared equivocal or lacked context. This indicates that AI, if not well integrated, may elevate rather than lessen cognitive load. Automation bias, where individuals trust an algorithm's results without carefully evaluating them, and algorithm aversion are types of decision stress. It is, therefore, important that healthcare systems adopt ways of integrating human decisions into the automation processes, primarily through using two-tier systems and alert systems that use the radiologist's experience to correlate with the level of certainty the AI gives.

5.2.5 Drivers for Adoption: Training, Familiarity, and Institutional Support

Professional development through courses explicitly focused on artificial intelligence was deemed the most effective of all the drivers. The participants who attended the workshops or courses related to using AI in clinical practice were more likely to feel comfortable using AI tools during clinical routine tasks. They also stated feeling more confident about diagnostic results and increased dependence on AI outputs. The other predictor that informed the switch was system transparency. Ignored tools did not offer confidence estimates, the paths to the final decision, or case references. These features supported efforts to narrow the gap between its ability to anticipate and consider a human clinician's judgement, thereby establishing more credibility. Others are explained as follows: Liquidity, familiarity and management of change, which enhances trust through pilot projects/ supervised implementation and reduces resistance. The institutional culture was also decisive. Organisations that received organisational sanction in terms of financial input and personnel participation in the structures aimed at integrating AI into radiology practices showcased better compliance with the approaches among radiologists. On the other hand, some facilities that introduced AI, when not well received or not well consulted on it, experienced a lot of pushback. Therefore, for the enhancement and eventual integration of artificial intelligence in society, applying a comprehensive education program, information systems transparency, and institutional preparation is imperative.

5.3 Contributions and Limitations of the Study

Thus, the study adds to the extant literature on AI implementation within clinical settings by combining quantitative data with qualitative discoveries. This shows that AI trust is a product of interpretability, compatibility with the flow of work, and previous experience, not merely efficiency. It also presents some issues, which have a structural, regulatory, as well as and ethical nature, that must be solved to realise AI to the full extent in medical imaging. The study aligns with the hypotheses postulated by the Technology Acceptance Model (TAM) or, more broadly, the Socio-Technical Systems Theory (STS), which demonstrates that AI is not just an organisational or technical solution but a socio-clinical revolution. When specific to the domain of cancer detection using MRI, the models unravel the interplay of people, work, and technology. However, some limitations are apparent. The sample size was statistically appropriate but small, covering only the Plains states and California. The reliance on self-reported data also introduces an issue with subjectivity. Moreover, it can be stated that the frequency of scientific publications varies, and the results may require constant updating due to the dynamism of AI technology. Longitudinal examination and more diverse and numerous samples could be collected to yield more generalizable conclusions.

5.4 Recommendations for Practice and Research

The research makes practical and academic recommendations for the future application and study of AI-assisted MRI in cancer detection. First, committed spending toward explainable AI systems must come from healthcare institutions. They should be high in diagnostic accuracy but also provide graphic and textual representations of their output and how they arrived at that conclusion. It will also boost transparency, improve trust in the coming regulations among radiologists, and support the latest regulatory requirements. In parallel, one should consider making the introductory AI courses for radiologists compulsory. These educational initiatives should be part of continuous professional development and focus more on the practical application of AI tools, analysis of results, and possible ethics. By raising awareness and improving the knowledge about AI systems among radiologists, such programs can make a substantial difference in the level of reassurance and specificity of clinical diagnoses.

Clear legal standards that detail approvals for AI use in medical diagnostics should be established as an immediate requirement. Health authorities at national and regional levels need to create systems which establish diagnostic error accountability guidelines for AI use while avoiding excessive responsibility for individual medical staff. Clear legal frameworks will boost institutional confidence in AI technology adoption. Healthcare facilities need to dedicate substantial effort to modernise their technological framework. Healthcare institutions maintain legacy systems which do not support current standards in AI platforms. Ethical governance requires integration into every step of AI system implementation. Before summarising the specific recommendations, it is necessary to say that institutions must implement external audits that accompany algorithmic fairness analysis, data privacy law compliance, and patients' rights to consent and data information. These protocols reduce ethical issues and increase public trust in AI-diagnosed treatment systems. Additional studies must examine the interaction dynamics between radiologists and AI systems in their daily work routines. Observational research will reveal extensive data about the role of AI in people's behavioural decisions, along with defining system decision-making and AI systems' secondary consequences. Research that involves comparing different AI platforms and understanding the patient's perception of AI when diagnosing would give a complete insight into the effects of AI on healthcare systems.

5.5 Final Reflections and Summary of the Chapter

The research journey enriched my knowledge and perception of medical ethics, technology, and their impact on clinical practice and patient's cerebral prowess. In this study, artificial intelligence healthcare features revealed tool prowess, and it showed why trust and mutual knowledge, complemented by the transparency of AI consideration, are essential for responsible advances in artificial intelligence. The partnership between AI systems and experienced human practitioners becomes necessary to harness artificial intelligence systems' early cancer detection capabilities. Developing AI applications in medical diagnosis established my life-long quest to invent technology that preserves providers' human dignity and professional relevance while providing necessary safety and well-being for their patients.

For AI-assisted MRI systems specifically for early cancer detection, one has to address the following factors: the visibility of the AI, integration into the work process, and, most importantly, the confidence of the radiologic professional. Radiologists are receptive to the use of AI as a supplementary tool regarding the appropriateness of its use in specific tasks and the legal constraints, along with the transparency of the system. This research advances practical and theoretical knowledge for the field while presenting specific steps that developers, regulators, and healthcare establishments should implement. More research must be conducted on a larger scale to get more information about the system and its users' usage behaviour. Safe cancer diagnostics advancements require AI to support human expertise rather than attempt to replace it.

References

Abdelwanis, M. *et al.* (2024) ‘Exploring the risks of automation bias in healthcare artificial intelligence applications: A Bowtie analysis’. *Journal of Safety Science and Resilience*. https://www.sciencedirect.com/science/article/pii/S2666449624000410

Adler-Milstein, J. *et al*. (2022) ‘Meeting the moment: addressing barriers and facilitating clinical adoption of artificial intelligence in medical diagnosis’. *NAM perspectives*, 2022, pp.10-31478. https://pmc.ncbi.nlm.nih.gov/articles/PMC9875857/

Ahmad, Z. *et al.* (2021) ‘Artificial intelligence (AI) in medicine, current applications and future role with special emphasis on its potential and promise in pathology: present and future impact, obstacles including costs and acceptance among pathologists, practical and philosophical considerations. A comprehensive review’. *Diagnostic pathology*, 16, pp.1-16. https://link.springer.com/article/10.1186/s13000-021-01085-4

Ahn, JS. *et al*. (2022) ‘Association of artificial intelligence–aided chest radiograph interpretation with reader performance and efficiency’. *JAMA Network Open*, 5(8), pp.e2229289-e2229289. https://jamanetwork.com/journals/jamanetworkopen/article-abstract/2795798

Albahri, AS. *et al.* (2023) ‘A systematic review of trustworthy and explainable artificial intelligence in healthcare: Assessment of quality, bias risk, and data fusion’. *Information Fusion*, 96, pp.156-191. https://www.sciencedirect.com/science/article/pii/S1566253523000891

Amann, J. *et al*. (2022) ‘To explain or not to explain?—Artificial intelligence explainability in clinical decision support systems’. *PLOS Digital Health*, 1(2), p.e0000016. https://journals.plos.org/digitalhealth/article?id=10.1371/journal.pdig.0000016

Bergmann, J. (2023) ‘Research philosophy, methodological implications, and research design’. In *At Risk of Deprivation: The Multidimensional Well-Being Impacts of Climate Migration and Immobility in Peru* (pp. 57-89). Wiesbaden: Springer Fachmedien Wiesbaden. https://link.springer.com/chapter/10.1007/978-3-658-42298-1_3

Bergquist, M. *et al.* (2024) ‘Trust and stakeholder perspectives on the implementation of AI tools in clinical radiology’. *European radiology*, 34(1), pp.338-347.

Borys, K. et al. (2023) ‘Explainable AI in medical imaging: An overview for clinical practitioners–Beyond saliency-based XAI approaches’. *European journal of radiology*, 162, p.110786. https://www.sciencedirect.com/science/article/pii/S0720048X23001006

Brady, AP. *et al.* (2024) ‘Developing, purchasing, implementing and monitoring AI tools in radiology: practical considerations. A multi-society statement from the ACR, CAR, ESR, RANZCR & RSNA’. *Canadian Association of Radiologists Journal*, 75(2), pp.226-244. https://journals.sagepub.com/doi/abs/10.1177/08465371231222229
Brady, AP. *et al.* (2024) ‘Developing, purchasing, implementing and monitoring AI tools in radiology: practical considerations. A multi-society statement from the ACR, CAR, ESR, RANZCR & RSNA’. *Canadian Association of Radiologists Journal*, 75(2), pp.226-244. https://journals.sagepub.com/doi/abs/10.1177/08465371231222229
Carriero, A. *et al.* (2024) ‘Deep learning in breast cancer imaging: State of the art and recent advancements in early 2024’. *Diagnostics*, 14(8), p.848. https://www.mdpi.com/2075-4418/14/8/848

Cash, P. *et al.* (2022) ‘Sampling in design research: Eight key considerations’. *Design studies*, 78, p.101077. https://www.sciencedirect.com/science/article/pii/S0142694X21000880

Chen, J. *et al.* (2023) ‘Investigating the impact of cognitive biases in radiologists’ image interpretation: A scoping review’. *European Journal of Radiology*, 166, p.111013. https://www.sciencedirect.com/science/article/pii/S0720048X23003273

Chen, Y. *et al.* (2021) ‘Professionals’ responses to the introduction of AI innovations in radiology and their implications for future adoption: a qualitative study’. *BMC health services research*, 21, pp.1-9.

Crotty, E. *et al.* (2024) ‘Artificial intelligence in medical imaging education: Recommendations for undergraduate curriculum development’. *Radiography*, 30, pp.67-73. https://www.sciencedirect.com/science/article/pii/S1078817424003067

Dawadi, S. *et al.* (2021) ‘Mixed-methods research: A discussion on its types, challenges, and criticisms’. *Journal of Practical Studies in Education*, 2(2), pp.25-36. https://oro.open.ac.uk/75449/

De Bruijn, H. *et al.* (2022) ‘The perils and pitfalls of explainable AI: Strategies for explaining algorithmic decision-making’. *Government information quarterly*, 39(2), p.101666. https://www.sciencedirect.com/science/article/pii/S0740624X21001027

Debs, P. and Fayad, LM. (2023) ‘The promise and limitations of artificial intelligence in musculoskeletal imaging’. *Frontiers in Radiology*, 3, p.1242902. https://www.frontiersin.org/articles/10.3389/fradi.2023.1242902/full

Durur-Subasi, I. and Özçelik, ŞB. (2023) 'Artificial intelligence in breast imaging: Opportunities, challenges, and legal–ethical considerations'. *The Eurasian Journal of Medicine*, 55(Suppl 1), p.S114. https://pmc.ncbi.nlm.nih.gov/articles/PMC11075018/

Eltawil, FA. *et al.* (2023) 'Analyzing barriers and enablers for the acceptance of artificial intelligence innovations into radiology practice: a scoping review'. *Tomography*, 9(4), pp.1443-1455. https://www.mdpi.com/2379-139X/9/4/115

Evans, BJ. (2023) 'Rules for robots, and why medical AI breaks them'. *Journal of Law and the Biosciences*, 10(1), p.lsad001. https://academic.oup.com/jlb/article-pdf/doi/10.1093/jlb/lsad001/49225082/lsad001.pdf

Evans, H. and Snead, D. (2024) 'Understanding the errors made by artificial intelligence algorithms in histopathology in terms of patient impact'. *NPJ Digital Medicine*, 7(1), p.89. https://www.nature.com/articles/s41746-024-01093-w

Fransen, SJ. *et al.* (2024) 'Patient perspectives on the use of artificial intelligence in prostate cancer diagnosis on MRI'. *European radiology*, pp.1-7. https://link.springer.com/article/10.1007/s00330-024-11012-y

Gallagher, C. (2024) *Mayo researchers invented a new class of AI to improve cancer research and treatments.* Available at: https://newsnetwork.mayoclinic.org/discussion/mayo-researchers-invented-a-new-class-of-ai-to-improve-cancer-research-and-treatments/ Accessed on: 24-March-2025

Ganesha, HR and Aithal, PS (2022) 'How to choose an appropriate research data collection method and method choice among various research data collection methods and method choices during Ph. D. program in India'. *International Journal of Management, Technology, and Social Sciences*, 7(2), pp.455-489. https://www.academia.edu/download/100063600/26._How_to_Choose_an_Appropriate_Research_Data.pdf

Ghanad, A. (2023) 'An overview of quantitative research methods'. *International journal of multidisciplinary research and analysis*, 6(08), pp.3794-3803. https://www.researchgate.net/profile/Anahita-Ghanad/publication/373370007_An_Overview_of_Quantitative_Research_Methods/links/67b28ffc645ef274a48341a1/An-Overview-of-Quantitative-Research-Methods.pdf

Gichoya, JW. *et al.* (2022) 'AI recognition of patient race in medical imaging: a modelling study'. *The Lancet Digital Health*, 4(6), pp.e406-e414. https://www.thelancet.com/journals/landig/article/PIIS2589-7500(22)00063-2/fulltext?ref=medicalnotes.co

Giovanola, B. and Tiribelli, S. (2023) 'Beyond bias and discrimination: redefining the AI ethics principle of fairness in healthcare machine-learning algorithms'. *AI & society*, 38(2), pp.549-563. https://link.springer.com/article/10.1007/s00146-022-01455-6

Goisauf, M. and Cano Abadía, M. (2022) 'Ethics of AI in radiology: a review of ethical and societal implications'. *Frontiers in big Data*, 5, p.850383. https://www.frontiersin.org/articles/10.3389/fdata.2022.850383/full

Göndöcs, D. and Dörfler, V. (2024) 'AI in medical diagnosis: AI prediction & human judgment'. *Artificial Intelligence in Medicine*, 149, p.102769. https://www.sciencedirect.com/science/article/pii/S0933365724000113

Guidance, WHO. (2021) 'Ethics and governance of artificial intelligence for health'. *World Health Organization*. https://iris.who.int/bitstream/handle/10665/341996/9789240029200-eng.pdf

Habuza, T. et al. (2021) 'AI applications in robotics, diagnostic image analysis and precision medicine: Current limitations, future trends, guidelines on CAD systems for medicine'. *Informatics in Medicine Unlocked*, 24, p.100596. https://www.sciencedirect.com/science/article/pii/S2352914821000861

Hager, T. and Hollsten, A. (2024) 'Leveraging Machine Learning Expertise for Healthcare Innovation: A Case Study in the Biomedical Market with Focus on Cervical Cancer Screening. https://lup.lub.lu.se/student-papers/search/publication/9165931

Haque, MS. (2022) 'Inductive and/or deductive research designs'. In *Principles of social research methodology* (pp. 59-71). Singapore: Springer Nature Singapore. https://link.springer.com/chapter/10.1007/978-981-19-5441-2_5

Hassan, S. (2025) 'Artificial Intelligence in Diagnostic Imaging: Enhancing Patient Care Through Advanced Algorithms and Data Integration'. https://www.preprints.org/frontend/manuscript/0aea29082d823467f6862b2ddf324104/download_pub

Huang, Y. and Gursoy, D. (2024) 'How does AI technology integration affect employees' proactive service behaviors? A transactional theory of stress perspective'. *Journal of Retailing and*

Consumer Services, 77, p.103700. https://www.sciencedirect.com/science/article/pii/S0969698923004514

Islam, MA and Aldaihani, FMF (2022) 'Justification for adopting qualitative research method, research approaches, sampling strategy, sample size, interview method, saturation, and data analysis'. *Journal of International Business and Management*, 5(1), pp.01-11. https://www.researchgate.net/profile/Md-Islam-394/publication/357352896_Justification_for_Adopting_Qualitative_Research_Method_Research_Approaches_Sampling_Strategy_Sample_Size_Interview_Method_Saturation_and_Data_Analysis/links/61c9ed5ab8305f7c4b05d50c/Justification-for-Adopting-Qualitative-Research-Method-Research-Approaches-Sampling-Strategy-Sample-Size-Interview-Method-Saturation-and-Data-Analysis.pdf

Ismail, NA. *et al* (2022) 'Assessment of epidemiological and genetic characteristics and clinical outcomes of resistance to bedaquiline in patients treated for rifampicin-resistant tuberculosis: a cross-sectional and longitudinal study'. *The Lancet infectious diseases*, 22(4), pp.496-506. https://www.thelancet.com/journals/laninf/article/PIIS1473-3099(21)00470-9/abstract

Jiang, Y. *et al.* (2021) 'Artificial intelligence applied to breast MRI for improved diagnosis'. *Radiology*, 298(1), pp.38-46.

Johannesson, P. *et al.* (2021) 'Research strategies and methods'. *An introduction to design science*, pp.41-75. https://link.springer.com/chapter/10.1007/978-3-030-78132-3_3

Johnson, WG. (2022) 'Flexible regulation for dynamic products? The case of applying principles-based regulation to medical products using artificial intelligence'. *Law, Innovation and Technology*, 14(2), pp.205-236. https://www.tandfonline.com/doi/abs/10.1080/17579961.2022.2113665

Keles, A. *et al.* (2023) 'Saliency Maps as an Explainable AI Method in Medical Imaging: A Case Study on Brain Tumor Classification. *Zenodo*. https://www.researchgate.net/profile/Ayse-Inan-Keles/publication/373392202_Saliency_Maps_as_an_Explainable_AI_Method_in_Medical_Imaging_A_Case_Study_on_Brain_Tumor_Classification/links/64e916e2434d3f628c4d5137/Saliency-Maps-as-an-Explainable-AI-Method-in-Medical-Imaging-A-Case-Study-on-Brain-Tumor-Classification.pdf

Khan, TH and MacEachen, E. (2022) 'An alternative method of interviewing: Critical reflections on videoconference interviews for qualitative data collection'. *International journal of qualitative* *methods*, 21, p.16094069221090063. https://journals.sagepub.com/doi/abs/10.1177/16094069221090063

Khogali, HO and Mekid, S. (2023) 'The blended future of automation and AI: Examining some long-term societal and ethical impact features'. *Technology in Society*, 73, p.102232. https://www.sciencedirect.com/science/article/pii/S0160791X23000374

Kieslich, K. *et al.* (2022) 'Artificial intelligence ethics by design. Evaluating public perception on the importance of ethical design principles of artificial intelligence'. *Big Data & Society*, 9(1), p.20539517221092956. https://journals.sagepub.com/doi/abs/10.1177/20539517221092956

Koçak, B. *et al.* (2025) 'Bias in artificial intelligence for medical imaging: fundamentals, detection, avoidance, mitigation, challenges, ethics, and prospects'. *Diagnostic and Interventional Radiology*, 31(2), p.75. https://pmc.ncbi.nlm.nih.gov/articles/PMC11880872/

Konnoth, C. (2024) 'AI and data protection law in health". In *Research Handbook on Health, AI and the Law* (pp. 111-129). Edward Elgar Publishing. https://www.elgaronline.com/edcollchap-oa/book/9781802205657/ch07.xml

Larson, DB. *et al.* (2021) 'Regulatory frameworks for development and evaluation of artificial intelligence–based diagnostic imaging algorithms: summary and recommendations'. *Journal of the American College of Radiology*, 18(3), pp.413-424. https://www.sciencedirect.com/science/article/pii/S1546144020310206

Lekadir, K. *et al.* (2021) 'FUTURE-AI: guiding principles and consensus recommendations for trustworthy artificial intelligence in medical imaging'. *arXiv preprint arXiv:2109.09658*. https://arxiv.org/abs/2109.09658

Lombi, L. and Rossero, E. (2024) 'How artificial intelligence is reshaping the autonomy and boundary work of radiologists. A qualitative study'. *Sociology of health & illness*, 46(2), pp.200-218. https://onlinelibrary.wiley.com/doi/abs/10.1111/1467-9566.13702

Mahedi, RA. *et al.* (2024) 'Current Trends and Future Prospects of Artificial Intelligence in Transforming Radiology'. *Journal of Current Health Sciences*, 4(2), pp.95-104.

Marey, A. *et al.* (2024) 'Explainability, transparency and black box challenges of AI in radiology: Impact on patient care in cardiovascular radiology'. *Egyptian Journal of Radiology and Nuclear Medicine*, 55(1), p.183. https://link.springer.com/article/10.1186/s43055-024-01356-2

Martin, C. *et al.* (2022) 'The ethical considerations including inclusion and biases, data protection, and proper implementation among AI in radiology and potential implications'. *Intelligence-Based Medicine*, 6, p.100073. https://www.sciencedirect.com/science/article/pii/S2666521222000266

Mata, LA. *et al.* (2021) 'Artificial intelligence–assisted prostate cancer diagnosis: Radiologic-pathologic correlation'. *Radiographics*, 41(6), pp.1676-1697. https://pubs.rsna.org/doi/abs/10.1148/rg.2021210020

Medium, 2021. *How Zebra Medical Vision Developed Clinical AI Solutions.* Available at: https://medium.com/data-science/how-zebra-medical-vision-developed-clinical-ai-solutions-34b385617b65 Accessed on: 24-March-2025

Mishra, SB and Alok, S. (2022) '*Handbook of research methodology'*. Educreation publishing. https://dspace.unitywomenscollege.ac.in/bitstream/123456789/1319/1/BookResearchMethodology.pdf

Morandini, S. *et al.* (2023) 'The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations'. *Informing Science*, 26, pp.39-68. https://cris.unibo.it/handle/11585/917132

Morley, J. et al. (2022) 'Governing data and artificial intelligence for health care: developing an international understanding'. *JMIR formative research*, 6(1), p.e31623. https://formative.jmir.org/2022/1/e31623

Najjar, R. (2023) 'Redefining radiology: a review of artificial intelligence integration in medical imaging'. *Diagnostics*, 13(17), p.2760. https://www.mdpi.com/2075-4418/13/17/2760

Nanthagopan, Y. (2021) 'Review and comparison of multi-method and mixed method application in research studies'. *Journal of Advanced Research,* 2(3), pp.55-78. https://www.ceeol.com/search/article-detail?id=1018520

Newman-Toker, DE. *et al.* (2021) 'Rate of diagnostic errors and serious misdiagnosis-related harms for major vascular events, infections, and cancers: toward a national incidence estimate using the "Big Three"'. *Diagnosis*, 8(1), pp.67-84. https://www.degruyter.com/document/doi/10.1515/dx-2019-0104/html?ref=geektime.com

Nichols, SR. *et al.* (2022) 'Factors That Impact Caseload and Case Acuity in Outpatient Mental Health and Family Maltreatment;. *Social Work Research,* 46(4), pp.280-292. https://academic.oup.com/swr/article-abstract/46/4/280/6762974

Oladele, OK. (2024) ‘Machine Learning Algorithms for Analyzing Medical Imaging and Improving Diagnostic Accuracy’. https://www.researchgate.net/profile/Oluwaseyi-Oladele-3/publication/387539424_Machine_Learning_Algorithms_for_Analyzing_Medical_Imaging_and_Improving_Diagnostic_Accuracy/links/67735308894c55208537e051/Machine-Learning-Algorithms-for-Analyzing-Medical-Imaging-and-Improving-Diagnostic-Accuracy.pdf

Oyeniyi, J. and Oluwaseyi, P. (2024) ‘Emerging trends in AI-powered medical imaging: enhancing diagnostic accuracy and treatment decisions’. *International Journal of Enhanced Research In Science Technology & Engineering*, 13, pp.2319-7463. https://www.researchgate.net/profile/Johnson-Oyeniyi/publication/379898576_Emerging_Trends_in_AI-Powered_Medical_Imaging_Enhancing_Diagnostic_Accuracy_and_Treatment_Decisions/links/6620e2ac66ba7e2359e64373/Emerging-Trends-in-AI-Powered-Medical-Imaging-Enhancing-Diagnostic-Accuracy-and-Treatment-Decisions.pdf

Pacurari, AC. et al. (2023) ‘Diagnostic accuracy of machine learning AI architectures in detection and classification of lung cancer: a systematic review’. *Diagnostics*, 13(13), p.2145. https://www.mdpi.com/2075-4418/13/13/2145

Passalacqua, M. *et al.* (2024) ‘Human-centred AI in industry 5.0: a systematic review’. *International Journal of Production Research*, pp.1-32. https://www.tandfonline.com/doi/abs/10.1080/00207543.2024.2406021

Pierre, K. *et al.* (2023) ‘Applications of artificial intelligence in the radiology roundtrip: process streamlining, workflow optimization, and beyond’. In *Seminars in roentgenology* (Vol. 58, No. 2, pp. 158-169). WB Saunders. https://www.sciencedirect.com/science/article/pii/S0037198X2300010X

Proudfoot, K. (2023) ‘Inductive/deductive hybrid thematic analysis in mixed methods research’. *Journal of mixed methods research*, 17(3), pp.308-326. https://journals.sagepub.com/doi/abs/10.1177/15586898221126816

Pul, U. and Schwendicke, F. (2024) ‘Artificial intelligence for detecting periapical radiolucencies: a systematic review and meta-analysis’. *Journal of Dentistry*, p.105104. https://www.sciencedirect.com/science/article/pii/S0300571224002732

Qureshi, A. *et al.* (2021) ‘The Promising Role of Artificial Intelligence in Navigating Lung Cancer Prognosis’. *International Journal for Multidisciplinary Research*, 6(4), pp.1-21.

https://www.researchgate.net/profile/Hamza-Qureshi/publication/383650705_The_Promising_Role_of_Artificial_Intelligence_in_Navigating_Lung_Cancer_Prognosis/links/66d55995bd201736676637af/The-Promising-Role-of-Artificial-Intelligence-in-Navigating-Lung-Cancer-Prognosis.pdf

Raghavan, K. *et al.* (2024) 'Explainable artificial intelligence for medical imaging: Review and experiments with infrared breast images'. *Computational Intelligence*, 40(3), p.e12660. https://onlinelibrary.wiley.com/doi/abs/10.1111/coin.12660

Rana, M. and Bhushan, M. (2023) 'Machine learning and deep learning approach for medical image analysis: diagnosis to detection'. *Multimedia Tools and Applications*, 82(17), pp.26731-26769. https://link.springer.com/article/10.1007/s11042-022-14305-w

Rani, U. *et al.* (2024).' *Algorithmic management practices in regular workplaces: case studies in logistics and healthcare'*. https://www.bollettinoadapt.it/wp-content/uploads/2024/02/wcms_913016.pdf

Robertson, C. *et al.* (2023) 'Diverse patients' attitudes towards Artificial Intelligence (AI) in diagnosis'. *PLOS Digital Health*, 2(5), p.e0000237. https://journals.plos.org/digitalhealth/article?id=10.1371/journal.pdig.0000237

Rosenbacke, R. *et al.* (2024) 'How Explainable Artificial Intelligence Can Increase or Decrease Clinicians' Trust in AI Applications in Health Care: Systematic Review'. *JMIR AI*, 3, p.e53207. https://ai.jmir.org/2024/1/e53207

Saliya, CA. (2023) 'Research Philosophy: Paradigms, world views, perspectives, and theories'. In *Social research methodology and publishing results: A guide to non-native English speakers* (pp. 35-51). IGI Global. https://www.igi-global.com/chapter/research- philosophy/320209

Shan, Y. (2022) 'Philosophical foundations of mixed methods research'. *Philosophy Compass*, 17(1), p.e12804. https://compass.onlinelibrary.wiley.com/doi/abs/10.1111/phc3.12804

Shen, FX. *et al.* (2024) 'Ethical, legal, and policy challenges in field-based neuroimaging research using emerging portable MRI technologies: guidance for investigators and for oversight'. *Journal of Law and the Biosciences*, 11(1), p.lsae008. https://academic.oup.com/jlb/article-abstract/11/1/lsae008/7689308

Shin, D. (2021) 'The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI'. *International journal of human-computer studies*, 146, p.102551. https://www.sciencedirect.com/science/article/pii/S1071581920301531

Singhal, A. *et al*. (2024) 'Explainable Artificial Intelligence (XAI) Model for Cancer Image Classification;. *CMES-Computer Modeling in Engineering & Sciences*, 141(1). https://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=15261492&AN=179281271&h=bhF9npCCyEXYpUrHHBV5%2BbGZ%2BQHw2WZUrI%2BS0AxY3GgtuukZObm7ZdwjqW6584fdjBf9Y2JaLUH5SHzKHqkMyw%3D%3D&crl=c

Stanford (2019) *AI could help radiologists interpret mammograms more accurately*. Available at: https://engineering.stanford.edu/news/ai-could-help-radiologists-interpret-mammograms-more-accurately Accessed on: 24-March-2025

Syer, T. *et al*. (2021) 'Artificial intelligence compared to radiologists for the initial diagnosis of prostate cancer on magnetic resonance imaging: a systematic review and recommendations for future studies'. *Cancers*, 13(13), p.3318. https://www.mdpi.com/2072-6694/13/13/3318

Taribagil, P. *et al.* (2023) 'Integrating artificial intelligence into an ophthalmologist's workflow: obstacles and opportunities'. *Expert Review of Ophthalmology*, 18(1), pp.45-56. https://www.tandfonline.com/doi/abs/10.1080/17469899.2023.2175672

Tariq, MU. (2025) 'AI-Powered Breakthroughs: Revolutionizing Cognitive Psychology and Neuropsychology With Machine Learning'. In *Transforming Neuropsychology and Cognitive Psychology With AI and Machine Learning* (pp. 65-92). IGI Global Scientific Publishing. https://www.igi-global.com/chapter/ai-powered-breakthroughs/367704

Tejani, AS. et al. (2024) 'Understanding and mitigating bias in imaging artificial intelligence'. *Radiographics*, 44(5), p.e230067. https://pubs.rsna.org/doi/abs/10.1148/rg.230067

Thakkar, S. *et al.* (2023) 'Artificial intelligence and real-world data for drug and food safety–a regulatory science perspective'. *Regulatory Toxicology and Pharmacology*, 140, p.105388. https://www.sciencedirect.com/science/article/pii/S0273230023000569

Thieme, A. *et al.* (2024) 'Challenges for responsible AI design and workflow integration in healthcare: a case study of automatic feeding tube qualification in radiology'. *ACM Transactions on Computer-Human Interaction*. https://dl.acm.org/doi/abs/10.1145/3716500

Tong, MW. *et al.* (2025) ‘Artificial intelligence in musculoskeletal applications: a primer for radiologists’. *Diagnostic and Interventional Radiology*, 31(2), p.89. https://pmc.ncbi.nlm.nih.gov/articles/PMC11880867/

Tsuneki, M. (2022) ‘Deep learning models in medical image analysis’. *Journal of Oral Biosciences*, 64(3), pp.312-320. https://www.sciencedirect.com/science/article/pii/S1349007922000500

Ungureanu, AM. *et al.* (2025) ‘Controversies in the Application of AI in Radiology—Is There Medico-Legal Support? Aspects from Romanian Practice’. *Diagnostics*, 15(2), p.230. https://www.mdpi.com/2075-4418/15/2/230

Van der Velden, BH. *et al.* (2022) ‘Explainable artificial intelligence (XAI) in deep learning-based medical image analysis’. *Medical Image Analysis*, 79, p.102470. https://www.sciencedirect.com/science/article/pii/S1361841522001177

Van Leeuwen, KG. *et al.* (2022) ‘How does artificial intelligence in radiology improve efficiency and health outcomes?’. *Pediatric radiology*, pp.1-7. https://link.springer.com/article/10.1007/s00247-021-05114-8

Verma, H. *et al.* (2021) ‘On improving physicians’ trust in AI: Qualitative inquiry with imaging experts in the oncological domain’. *BMC Medical Imaging, in review*. https://pdfs.semanticscholar.org/8497/a2a1b8c1ad9726c0bfbff7880408106d61ce.pdf

Zaman, Q. (2024) ‘The role of artificial intelligence in early disease detection: transforming diagnostics and treatment’. *Multidisciplinary Journal of Healthcare (MJH)*, 1(2), pp.43-54. https://www.researchcorridor.org/index.php/mjh/article/view/52

Zhang, J. *et al.* (2024) ‘How AI and robotics will advance interventional radiology: narrative review and future perspectives’. *Diagnostics*, 14(13), p.1393. https://www.mdpi.com/2075-4418/14/13/1393

Zhang, L. *et al.* (2023) ‘Diagnostic error and bias in the department of radiology: a pictorial essay’. *Insights into Imaging*, 14(1), p.163. https://link.springer.com/article/10.1186/s13244-023- 01521-7

Appendices

Appendix 1: Ethics application and declaration form

Ethics Application & Declaration Form

DISSERTATION TITLE: Evaluation of AI-Assisted MRI in Early Cancer Detection: benefits, barriers and drivers for Radiologist Work Efficiency and Trust in AI

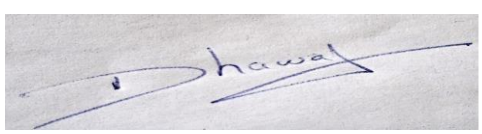
RESEARCHER'S NAME: DHAWAL SHINDE
PROGRAMME OF STUDY: M.Sc. IN MEDICAL DEVICE TECHNOLOGY AND BUSINESS
SUPERVISOR'S NAME: BRIAN KEARNEY

DECLARATION:

The information in this application form is accurate to the best of my knowledge. I undertake to abide by the principles outlined by Innopharma/Griffith College ethics policy in my research dissertation. I confirm that I have completed a full ethics assessment for my research dissertation as per the college guidelines. I will not begin my primary research until such approval from my supervisor and/or ethics Committee has been obtained.

I pledge to carry out my research according to the Innopharma/Griffith College academic integrity standards. Any results presented in my dissertation will be from my own, original research, I will reference and/or acknowledge any material or sources used in its preparation and I will not plagiarise the work of anyone else.

For Student:

STUDENT SIGNATURE: 

DATE: 28/03/2025

The research contained within this research dissertation proposal has been approved.

For Supervisor:

Ethics Committee Approval Required: Yes ☐ No ☒ x

SUPERVISOR SIGNATURE: Brian Kearney

DATE: 28 03 2025

NOTE: Supervisors are responsible for ensuring their students fill in this form correctly and that all ethical areas have been considered.

SECTION 1: DESCRIPTION OF RESEARCH STUDY

1.1 Purpose and objectives of research

This research investigates AI-assisted MRI for early cancer detection by studying how it benefits practices and what obstacles exist as well as the organizational motivators that drive its implementation in clinical radiology workflows. AI technology demonstrates capability to improve diagnostics through anomaly detection of human-radiologist missed abnormalities along with decreased interpretation times and minimized diagnostic errors. The automation of regular tasks via AI technology lets radiologists concentrate on difficult cases so they increase their workflow productivity. The broad implementation of AI in radiology remains limited because healthcare professionals maintain doubts about AI reliability as well as its interpretive capabilities and algorithm-generated biases. Doctors within the field of radiology commonly doubt AI systems when it comes to meeting human diagnostic capabilities especially with complicated cases which demand situational comprehension. Radiologists question using AI-assisted diagnosis because opaque AI models do not expose their workings thus creating ethical challenges that reduce confidence in these AI tools.

The research examines how radiologists feel about using AI for early cancer detection through MRI and evaluates how XAI models impact their trust in AI technology. The analysis evaluates human radiologist-perceived AI capabilities and thought accuracy when making clinical decisions compared to human diagnostics and their resulting impact on diagnosis confidence. The research investigates the organizational obstacles that prevent AI adoption which stem from regulatory complications and medical liability threats alongside human cognitive preferences about implementing AI systems. The study analyzes how AI-enabled MRI systems affect operative efficiency and mental labor by assessing whether automation increases productivity rates or requires added mental labor to confirm results. This research investigates ways to optimize AI application in radiology through its examination of human expertise protection so AI services advance healthcare results .

1.2 Research methodology

The research design incorporates both quantitative measures and qualitative data collection methods to completely evaluate AI-assisted MRI in early cancer detection. The researcher will conduct their primary data collection using online surveys and semi-structured interviews with both radiologists and healthcare professionals operating AI-integrated MRI systems.

An established web survey will obtain numerical data through 50-100 healthcare professionals who practice oncology and diagnostic imaging. Participants will rate their views about AI accuracy and reliability while providing their assessment of workflow efficiency and the trustworthiness of AI-assisted MRI using a 1 to 5 Likert-scale format. The research survey will reach various radiology specialists through their professional networks and LinkedIn professional connections to collect data from a wide selection of healthcare experts. The research will include board-certified radiologists who maintain at least one year of experience in utilizing AI-assisted MRI tools.

There will be 5 to 10 semi-structured interviews with radiologists from hospitals and diagnostic centers which actively incorporate AI into their MRI procedures. Open-ended questions in the interviews seek to uncover detailed information about radiologists' experiences and their biases toward AI along with their trust issues and obstacles they face in the adoption process. The research will utilize a snowball sampling method that expands participant recruitment through professional referral networks starting from existing radiologists. The interview period will take up to 30-45 minutes of face-to-face or virtual time.

The study selects participants who are both expert in MRI detection of cancer and have experience working with AI assistance tools. Doctor developers who lack clinical radiology experience will not qualify for participation because it does not meet the requirement of relevance. The study's participants must give their informed consent while the research team will safeguard data confidentiality during the entire investigation. The research design incorporates mixed methods to create an extensive comprehension of trust dynamics alongside workflow impacts and ethical considerations which emerge when AI enters radiological practice.

SECTION 2: POSSIBLE ETHICAL ISSUES

Answer 'yes' or 'no' to the following questions.

SUBJECT MATTER

Does the research proposal involve:

Research into specific company activities that would be deemed sensitive or confidential	No
Research into politically and/or racially/ethnically and/or commercially sensitive areas	No
Sensitive, personal, professional or corporate issues	No

RESEARCH PROCEDURES

Does the research proposal involve:

Research that might damage the reputation of companies or participants	No
Research that may negatively affect the reputation of Griffith College/Innopharma	No
Use of personal records without consent	No
Use of company data without consent	No
The offer of any inducements to participate	No
Audio or visual recording without consent	No
Using a language other than English	No

PARTICIPANTS

Does the research proposal involve:

People who are not competent and/or fluent in English	No
Does your research group include any of the following vulnerable groups	No

(Adults with psychological impairments; Adults with learning difficulties; Adults under the protection/control /influence of others (e.g. in care/prison); Relatives of ill people (e.g. parents of sick children); Hospital or GP participants recruited in a medical facility; persons under the age of 18)

<u>If you have answered NO to ALL questions, please go straight to Section 4.</u>

<u>If you have answered YES to ANY question in SECTION 2, you must fill in SECTION 3.</u>

SECTION 3: STEPS TAKEN TO AVOID ETHICAL ISSUES

[Only fill in this section if you answered YES to ANY of the questions in Section 3. For example, if you answered yes to including participants who are not fluent in English, you might put forward a plan that offers your survey in two languages to take this into account. Another example could be a study where the researcher wants to include information about the

care received by children with a long-term condition but it would not be ethical to approach the children directly but it might be acceptable to instead ask parents questions about their child's care. If these plans are acceptable to your supervisor, you may not need to apply for ethical approval from the Ethics Committee].

3.1. If your ethics relates to ***Subject Matter***, outline your action plan to work around any sensitive issues.
3.2. If your ethics relates to ***Research Procedures***, outline your action plan to deal with possible ethical issues in your research procedures.
3.3. If your ethics relates to ***Participants***, outline how you will protect vulnerable persons or those that do not have English as their first language.

SECTION 4: ABOUT YOUR PARTICIPANTS

4.1. Outline your participant profile and why you have chosen them for this study *[Do not provide names except where it is deemed impossible to conceal identity].*

Board-certified radiologists along with healthcare professionals specializing in oncology and diagnostic imaging who have worked with AI-assisted MRI systems for at least one year will constitute the study participants. Healthcare professionals with extensive expertise in AI technology have been selected because of their valuable knowledge regarding AI diagnostic performance along with operational enhancements and user trust towards AI implementation in medical facilities.

4.2 How do you plan to gain access to/contact/approach your participant(s).
Recruitment of participants will occur through networking within radiology professionals and LinkedIn groups while referrals through snowball sampling contribute to participant acquisition. Participants will receive study information through email or professional networks which includes details about the research goal along with consent policies and privacy terms to bring forward willing volunteers.

SECTION 5: INFORMATION, CONSENT AND CONFIDENTIALITY

5.1 **Participant Information Letter (PIL) for participants**

[You must submit an information letter for participants with this application, as part of your appendices document. For online surveys, it is sufficient to include a paragraph summarising and explaining the purpose of the research at the beginning of the survey. In all other research e.g. interviews, phonecalls, a PIL should be provided to each participant before they are asked for their consent to take part. A template PIL is available in Moodle].

Please confirm below that your information letter covers:

Description of the research topic and method	Yes
Details of what participation will involve	Yes
Rights to anonymity	Yes
Confidentiality	Yes
Rights to withdraw from the research	Yes
The contact details of the researcher and supervisor (if necessary)	Yes

5.2 **Informed Consent Form (ICF) for participants**

[Informed consent is required for most research. For online surveys, it is sufficient to get the participant to tick two boxes at the beginning of the survey – one to state they understand the research and one to give consent. In all other research e.g. interviews, phonecalls, a signed consent form is required. If the data is gathered online e.g. zoom, a signed consent form can be scanned and sent to the researcher. A template ICF is available in Moodle. The signed ICFs, along with the surveys, audio files or interview notes etc. must be stored in the primary data folder on moodle and can be accessed by Innopharma staff for the purposes of verifying the authenticity of the research carried out and the data collected].

Please indicate below if your research requires a signed consent form by selecting the relevant option only:

Yes: my research requires signed consent and I have attached an ICF in the appendices of my application.

SECTION 6: STORAGE OF DATA

[Please ensure that you are abiding by GDPR and the national Data protection laws https://www.hrb.ie/funding/gdpr-guidance-for-researchers/gdpr-and-health-research/).

*The student is responsible for storage of data and this will be handed over to the college in an electronic format as part of the thesis submission i.e. primary data and completed ICFs where applicable will be added to the primary data folder on moodle. The rationale is to keep data **as long as it is still useful** and there is an intention to use it further **for research** so if this is not the case then this can be stipulated here and a shorter retention period given.]*

6.1. How will you store the research data and for how long? How will you manage data protection issues?

The research data will be stored securely through encryption techniques in digital format on devices which require entry passwords for access protection. The collected information through Consent forms along with survey responses and interview transcripts will receive anonymization procedures to ensure participant confidentiality. The retention period will extend to five years after which all information must be destroyed based on GDPR regulations together with institutional standards. The storage period ends after five years when all collected data will be permanently erased to maintain compliance with ethical standards and data protection rules.

SECTION 7: NON-DISCLOSURE AGREEMENT & STUDENT CONSENT

7.1 **Non-Disclosure Agreement (NDA)**

Will the final dissertation contain any information pertaining to any source what would warrant the use of a Non-Disclosure Agreement (NDA) e.g. industry-based research?

Yes No

7.2 **Student consent**

If a Non-Disclosure Agreement (NDA) is not required, does the Student consent to allow their completed dissertation to be held/published by Innopharma/Griffith College?

Yes No

SECTION 8: RECORDING AND RETENTION OF DISSERTATION VIVA

8.1 **Viva Recording**

The Dissertation viva will be recorded. This recording may be used to facilitate assessment by Innopharma staff, a third reader if necessary and/or if requested by the external examiner for the Programme. The recording will be held in line with current GDPR guidelines and will not be made publicly available.

SECTION 9: DOCUMENT CHECKLIST

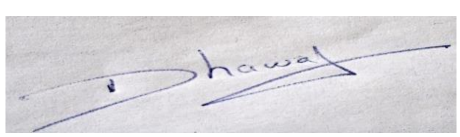
NOTE: Applicants must attach the following documents in electronic format to the appendix.

Which documents are added to the appendix? Please tick N/A if not applicable:

9.1 Participant Information Letter (PIL) for participant	Yes
9.2 Informed Consent Form (ICF) for participant	Yes
9.3 Questions/survey for interviewees/focus groups etc *(can be in draft form)*	Yes
9.4 Any other documents e.g. Non-Disclosure Agreement	N/A

I confirm that this application is complete and all required documents are included in the appendix.

For Student:

STUDENT SIGNATURE: 

DATE: 28/03/2025

Appendix 2: Signed consent form

Consent to take part in research

Evaluation of AI-Assisted MRI in Early Cancer Detection: benefits, barriers and drivers for Radiologist Work Efficiency and Trust in AI

The researcher retains one copy signed by both themselves and the participant. The participant should also receive a copy of consent form as a record of what they have signed up to.

- I [*insert participant name*] voluntarily agree to participate in this research study
- I understand that even if I agree to participate now, I can withdraw at any time or refuse to answer any question without any consequences of any kind
- I understand that I can withdraw permission to use data from my interview within two weeks after the interview, in which case the material will be deleted.
- I have had the purpose and nature of the study explained to me in writing and I have had the opportunity to ask questions about the study
- I understand that participation involves the interview of 30-45 minutes through semi-structured inquiry. The interview assessments will delve into my personal experiences with AI-assisted MRI and my current perceptions and trust of its implementation as well as my specific challenges and concerns regarding AI usage in clinical medicine.
- I understand that I will not benefit directly from participating in this research
- I understand that all information I provide for this study will be treated confidentially
- I understand that in any report on the results of this research my identity will remain anonymous. This will be done by changing my name and disguising any details of my interview which may reveal my identity or the identity of people I speak about.
- I agree to my interview being audio-recorded for the purpose of ensuring accurate transcription and analysis. I understand that the audio recording will be securely stored and only accessible to the researcher, with all identifying information removed during transcription.

- I understand that disguised extracts from my interview may be quoted in dissertation, which will be submitted to Griffith College and may be made available in the college library. The findings may also be presented at academic conferences, included in published papers, and potentially shared in online repositories or e-journals.
- I understand that if I inform the researcher that myself or someone else is at risk of harm, they may have to report this to the relevant authorities - they will discuss this with me first but may be required to report with or without my permission
- I understand that signed consent forms and original audio recordings will be retained in a secure, password-protected digital format on a password-protected device, accessible only to the researcher and supervisor. The data will be retained until the exam board confirms the results of my dissertation, after which the audio recordings will be permanently deleted.
- I understand that a transcript of my interview in which all identifying information has been removed will be retained for for two years from the date the exam board confirms the results of my dissertation
- I understand that under freedom of information legalisation I am entitled to access the information I have provided at any time while it is in storage as specified above.
- I understand that I am free to contact any of the people involved in the research to seek further clarification and information.

Researcher Details

Name – Dhawal Shinde
Degree Programme – Master of science in medical device technology and business
College Details – Griffith College Dublin
Contact number - 0892574696
Contact mail – shindedhawal.1998@gmail.com

Signature of participant

[Full Name – Printed]

Signature of research participant

-     - - - - - - - - - - - - - Date

Signature of researcher

I believe the participant is giving informed consent to participate in this study

----------------------------   --------------- Date

Signature of researcher

Appendix 3: Participant information letter

GRIFFITH COLLEGE

Participant Information Letter

Title - Evaluation of AI-Assisted MRI in Early Cancer Detection: benefits, barriers and drivers for Radiologist Work Efficiency and Trust in AI

I would like to invite you to take part in a research study. Before you decide you need to understand why the research is being done and what it would involve for you. Please take time to read the following information carefully. Ask questions if anything you read is not clear or if you would like more information. Take time to decide whether or not to take part.

WHO I AM AND WHAT THIS STUDY IS ABOUT

My name is Dhawal, and I am conducting this research as part of my Master of Science in medical device technology and business at Griffith College. This research examines how AI-assisted MRI affects early cancer detection by exploring advantages together with challenges and enabling factors which determine radiologists' trust in AI technology adoption. The research studies the effects of integrating AI on diagnostic precision together with workflow performance and medical practitioner mental workload in clinical environments. Your input supports the collection of important information needed to enhance AI implementation in radiology practice with reliable ethical standards.

WHAT WOULD TAKING PART INVOLVE?

The research requires participants to complete either a brief 10 to 15-minute online survey or in-depth interviews lasting between thirty to forty-five minutes. The questionnaire evaluates your perspective on MRI support from AI but the interview focuses on how you interact with AI systems and what trust issues and concerns you have regarding integration.

WHY HAVE YOU BEEN INVITED TO TAKE PART?

Your participation in this research project is based on your board certification as a radiologist or your role as an oncology specialist or diagnostic imaging professional and your experience working with AI-assisted MRI systems. Your professional perspective on the influence of AI on imaging diagnosis precision along with workflow optimization and medical professional trust is needed for this study.

DO YOU HAVE TO TAKE PART?

The study allows complete freedom for participants to choose whether they want to join. The study allows you to decline involvement or miss questions or terminate participation at any phase without justification and with no penalties. Prepare a contact with the researcher if you want to withdraw from this study.

WHAT ARE THE POSSIBLE RISKS AND BENEFITS OF TAKING PART?

Joining this study raises very few concerns about potential dangers. Discussions about work experiences with AI systems might lead to minor feelings of discomfort and worries regarding AI implementation. Investigations that utilize study findings help optimize radiology AI implementation and operational efficiency along with developing trust and ethical standards which result in benefits for both clinical staff and patient healthcare.

WILL TAKING PART BE CONFIDENTIAL?

The research team will maintain complete privacy about all participants' information. The research team will process all collected data through complete anonymization procedures without revealing any personal details. The data will be securely stored and the researcher will have exclusive access for retrieval. The researcher can disclose information outside the strict confidentiality rules only when there is severe potential harm to safety or when evidence reveals criminal actions.

HOW WILL INFORMATION YOU PROVIDE BE STORED AND PROTECTED?

The study data will be safely stored in encoded digital files which reside on password-protected storage systems. Recordings along with consent documents will be maintained until graduation but anonymized transcripts remain stored for two complete years. Researcher and supervisor possess exclusive entry to these documents.

WHAT WILL HAPPEN TO THE RESULTS OF THE STUDY?

I will use the research findings to fulfill the MSc dissertation requirements at Griffith College. The dissertation has potential placement in both the college library system and internet repositories. Academic conferences and future research will utilize findings obtained from this study.

WHO SHOULD YOU CONTACT FOR FURTHER INFORMATION?

[Dhawal Shinde , Phone – 0892574696 , Email – shindedhawal.1998@gmail.com .]

[THANK YOU]

Appendix 4: survey questions

1. What is your age group?

- 18 – 24
- 25 – 30
- 31 – 45
- Above 45

2. What is your current professional designation?

- Radiologist
- Oncologist
- Diagnostic Imaging Specialist
- AI Researcher or Developer in Medical Imaging

3. How many years of experience do you have in your current role?

- Less than 1 year
- 1-3 years
- 4-7 years
- 8-10 years
- More than 10 years

4. Have you used AI-assisted MRI systems in your clinical practice?

- Yes
- No
- I am aware of AI-assisted MRI but have not used it

5. How would you rate your familiarity with AI-assisted MRI systems?

- Very Familiar
- Somewhat Familiar
- Neutral
- Slightly Familiar
- Not Familiar

6. Do you believe AI-assisted MRI systems improve diagnostic accuracy?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

7. How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?

- Very Confident
- Moderately Confident
- Neutral
- Slightly Confident
- Not Confident

8. Do you feel AI-assisted MRI reduces your complete workload?

- Strongly Agree

- Agree
- Neutral
- Disagree
- Strongly Disagree

9. Does the use of AI-assisted MRI free up time for more complex cases?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

10. How much does AI-assisted MRI help reduce the likelihood of diagnostic errors?

- Significantly Reduces
- Moderately Reduces
- No Impact
- Slightly Increases
- Significantly Increases

11. Do you believe AI-assisted MRI reduces the risk of radiologist burnout?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

12. What are the primary barriers to adopting AI-assisted MRI in your institution?

- Lack of trust in AI results
- High cost of implementation
- Regulatory and compliance concerns
- Ethical and legal concerns
- Resistance from healthcare professionals

13. Do you feel that the “black-box” nature of AI algorithms affects your trust in AI-assisted MRI?

- Strongly Agree

- Agree
- Neutral
- Disagree
- Strongly Disagree

14. How confident are you in the regulatory frameworks governing AI use in MRI?

- Very Confident
- Somewhat Confident
- Neutral
- Slightly Confident
- Not Confident

15. Do you believe AI-assisted MRI presents important ethical concerns regarding patient privacy?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

16. Do you think AI approvals should always require human verification before making final decisions?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

17. What improvements would inspire you to adopt AI-assisted MRI more confidently?

- Better interpretability and explainability of AI decisions
- Stronger regulatory frameworks and standards
- More AI training for radiologists
- Reduced costs of implementation

18. Do you believe AI-specific training programs can increase trust and adoption of AI-assisted MRI?

- Strongly Agree

- Agree
- Neutral
- Disagree
- Strongly Disagree

Appendix 5: Interview questions

1. How has your experience been with integrating AI-assisted MRI systems into your clinical practice?
2. What factors influence your level of trust in AI-assisted MRI results?
3. What specific tasks or procedures in MRI diagnostics do you feel AI improves or enhances?
4. How do you identify the accuracy and reliability of AI-assisted MRI systems compared to human radiologists?
5. What challenges or concerns have you met when adopting AI-assisted MRI systems?
6. Do you think AI integration enhances cognitive workload or comforts the burden in your everyday workflow? Why?
7. How do you feel about the present regulatory frameworks leading the usage of AI in MRI diagnostics?
8. Are there any ethical or legal concerns that make you cautious about using AI-assisted MRI in clinical surroundings?
9. In your opinion, what enhancements or alterations would increase your trust and willingness to accept AI in MRI-based cancer detection?
10. Do you think targeted AI training programs could progress radiologists' acceptance and confidence in AI-assisted MRI? Why or why not?

Appendix 7: SPSS output

Descriptive Analysis

Frequencies

Statistics

cs

		What is your age group?	What is your current professional designation?	How many years of experience do you have in your current role?	Have you used AI-assisted MRI systems in your clinical practice?	How would you rate your familiarity with AI-assisted MRI systems?	Do you believe AI-assisted MRI systems improve diagnostic accuracy?	How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?	Do you feel AI-assisted MRI reduces your complete workload?	Does the use of AI-assisted MRI free up time for more complex cases?	How much does AI-assisted MRI help reduce the likelihood of diagnostic errors?	Do you believe AI-assisted MRI reduces the risk of radiologist burnout?	What are the primary barriers to adopting AI-assisted MRI in your institution?	Do you feel that the “black-box” nature of AI algorithms affects your trust in AI-assisted MRI?	How confident are you in the regulatory frameworks governing AI use in MRI?	Do you believe AI-assisted MRI presents important ethical concerns regarding patient privacy?	Do you think AI approvals should always require human verification before making final decisions?	What improvements would inspire you to adopt AI-assisted MRI more confidently?	Do you believe AI-specific training programs can increase trust and adoption of AI-assisted MRI?	
N	Valid	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72		72	72

Missing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean	2.31	2.49	2.54	2.19	2.53	2.46	2.26	2.39	2.50	2.33	2.47	2.63	2.71	2.65	2.53	2.64	2.28	2.63
Std. Error of Mean	.106	.134	.140	.096	.131	.130	.136	.146	.130	.122	.130	.140	.139	.128	.136	.147	.112	.150
Median	2.00	2.50	3.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.50	3.00	2.50	2.00	2.00	2.00
Mode	2	1	3	3	2	2	2	2	2	2	2	2	2	2	3	2	3	2
Std. Deviation	.898	1.138	1.186	.816	1.113	1.100	1.151	1.240	1.101	1.035	1.100	1.192	1.180	1.090	1.150	1.248	.953	1.272
Variance	.807	1.296	1.407	.666	1.239	1.210	1.324	1.537	1.211	1.070	1.210	1.421	1.393	1.188	1.323	1.558	.908	1.618
Skewness	.189	.006	.341	-.376	.590	.436	.944	.855	.522	.462	.660	.310	.276	.200	.330	.590	.113	.535
Std. Error of Skewness	.283	.283	.283	.283	.283	.283	.283	.283	.283	.283	.283	.283	.283	.283	.283	.283	.283	.283
Kurtosis	-.688	-1.401	-.638	-1.398	-.206	-.488	.250	-.091	-.305	-.598	.016	-.983	-.898	-.700	-.625	-.462	-.969	-.832
Std. Error of Kurtosis	.559	.559	.559	.559	.559	.559	.559	.559	.559	.559	.559	.559	.559	.559	.559	.559	.559	.559
Range	3	3	4	2	4	4	4	4	4	4	4	4	4	4	4	4	3	4
Minimum	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Maximum	4	4	5	3	5	5	5	5	5	5	5	5	5	5	5	5	4	5
Sum	166	179	183	158	182	177	163	172	180	168	178	189	195	191	182	190	164	189
Percentiles 25	2.00	1.00	2.00	1.25	2.00	2.00	1.00	1.25	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.25	2.00
Percentiles 50	2.00	2.50	3.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.50	3.00	2.50	2.00	2.00	2.00
Percentiles 75	3.00	3.75	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	4.00	4.00	3.00	3.00	3.00	3.00	4.00

Frequency Table

What is your age group?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18 – 24	14	19.4	19.4	19.4
	25 – 30	29	40.3	40.3	59.7
	31 – 45	22	30.6	30.6	90.3
	Above 45	7	9.7	9.7	100.0
	Total	72	100.0	100.0	

What is your current professional designation?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Radiologist	19	26.4	26.4	26.4
	Oncologist	17	23.6	23.6	50.0
	Diagnostic Imaging Specialist	18	25.0	25.0	75.0
	AI Researcher or Developer in Medical Imaging	18	25.0	25.0	100.0
	Total	72	100.0	100.0	

How many years of experience do you have in your current role?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 1 year	17	23.6	23.6	23.6
	1-3 years	18	25.0	25.0	48.6

		Frequency	Percent	Valid Percent	Cumulative Percent
	4-7 years	23	31.9	31.9	80.6
	8-10 years	9	12.5	12.5	93.1
	More than 10 years	5	6.9	6.9	100.0
	Total	72	100.0	100.0	

Have you used AI-assisted MRI systems in your clinical practice?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	18	25.0	25.0	25.0
	No	22	30.6	30.6	55.6
	I am aware of AI-assisted MRI but have not used it	32	44.4	44.4	100.0
	Total	72	100.0	100.0	

How would you rate your familiarity with AI-assisted MRI systems?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very Familiar	12	16.7	16.7	16.7
	Somewhat Familiar	28	38.9	38.9	55.6
	Neutral	19	26.4	26.4	81.9
	Slightly Familiar	8	11.1	11.1	93.1
	Not Familiar	5	6.9	6.9	100.0
	Total	72	100.0	100.0	

Do you believe AI-assisted MRI systems improve diagnostic accuracy?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	15	20.8	20.8	20.8
	Agree	25	34.7	34.7	55.6
	Neutral	19	26.4	26.4	81.9
	Disagree	10	13.9	13.9	95.8
	Strongly Disagree	3	4.2	4.2	100.0
	Total	72	100.0	100.0	

How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very Confident	19	26.4	26.4	26.4
	Moderately Confident	31	43.1	43.1	69.4
	Neutral	11	15.3	15.3	84.7
	Slightly Confident	6	8.3	8.3	93.1
	Not Confident	5	6.9	6.9	100.0
	Total	72	100.0	100.0	

Do you feel AI-assisted MRI reduces your complete workload?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	18	25.0	25.0	25.0
	Agree	28	38.9	38.9	63.9
	Neutral	14	19.4	19.4	83.3
	Disagree	4	5.6	5.6	88.9
	Strongly Disagree	8	11.1	11.1	100.0

	Total	72	100.0	100.0	

Does the use of AI-assisted MRI free up time for more complex cases?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	13	18.1	18.1	18.1
	Agree	27	37.5	37.5	55.6
	Neutral	19	26.4	26.4	81.9
	Disagree	9	12.5	12.5	94.4
	Strongly Disagree	4	5.6	5.6	100.0
	Total	72	100.0	100.0	

How much does AI-assisted MRI help reduce the likelihood of diagnostic errors?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Significantly Reduces	16	22.2	22.2	22.2
	Moderately Reduces	29	40.3	40.3	62.5
	No Impact	15	20.8	20.8	83.3
	Slightly Increases	11	15.3	15.3	98.6
	Significantly Increases	1	1.4	1.4	100.0
	Total	72	100.0	100.0	

Do you believe AI-assisted MRI reduces the risk of radiologist burnout?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	13	18.1	18.1	18.1

		Frequency	Percent	Valid Percent	Cumulative Percent
	Agree	28	38.9	38.9	56.9
	Neutral	20	27.8	27.8	84.7
	Disagree	6	8.3	8.3	93.1
	Strongly Disagree	5	6.9	6.9	100.0
	Total	72	100.0	100.0	

What are the primary barriers to adopting AI-assisted MRI in your institution?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of trust in AI results	13	18.1	18.1	18.1
	High cost of implementation	26	36.1	36.1	54.2
	Regulatory and compliance concerns	12	16.7	16.7	70.8
	Ethical and legal concerns	17	23.6	23.6	94.4
	Resistance from healthcare professionals	4	5.6	5.6	100.0
	Total	72	100.0	100.0	

Do you feel that the "black-box" nature of AI algorithms affects your trust in AI-assisted MRI?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	11	15.3	15.3	15.3
	Agree	25	34.7	34.7	50.0
	Neutral	15	20.8	20.8	70.8
	Disagree	16	22.2	22.2	93.1
	Strongly Disagree	5	6.9	6.9	100.0
	Total	72	100.0	100.0	

How confident are you in the regulatory frameworks governing AI use in MRI?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very Confident	11	15.3	15.3	15.3
	Somewhat Confident	23	31.9	31.9	47.2
	Neutral	21	29.2	29.2	76.4
	Slightly Confident	14	19.4	19.4	95.8
	Not Confident	3	4.2	4.2	100.0
	Total	72	100.0	100.0	

Do you believe AI-assisted MRI presents important ethical concerns regarding patient privacy?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	16	22.2	22.2	22.2
	Agree	20	27.8	27.8	50.0
	Neutral	22	30.6	30.6	80.6
	Disagree	10	13.9	13.9	94.4
	Strongly Disagree	4	5.6	5.6	100.0
	Total	72	100.0	100.0	

Do you think AI approvals should always require human verification before making final decisions?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	13	18.1	18.1	18.1

		Frequency	Percent	Valid Percent	Cumulative Percent
	Agree	24	33.3	33.3	51.4
	Neutral	21	29.2	29.2	80.6
	Disagree	4	5.6	5.6	86.1
	Strongly Disagree	10	13.9	13.9	100.0
	Total	72	100.0	100.0	

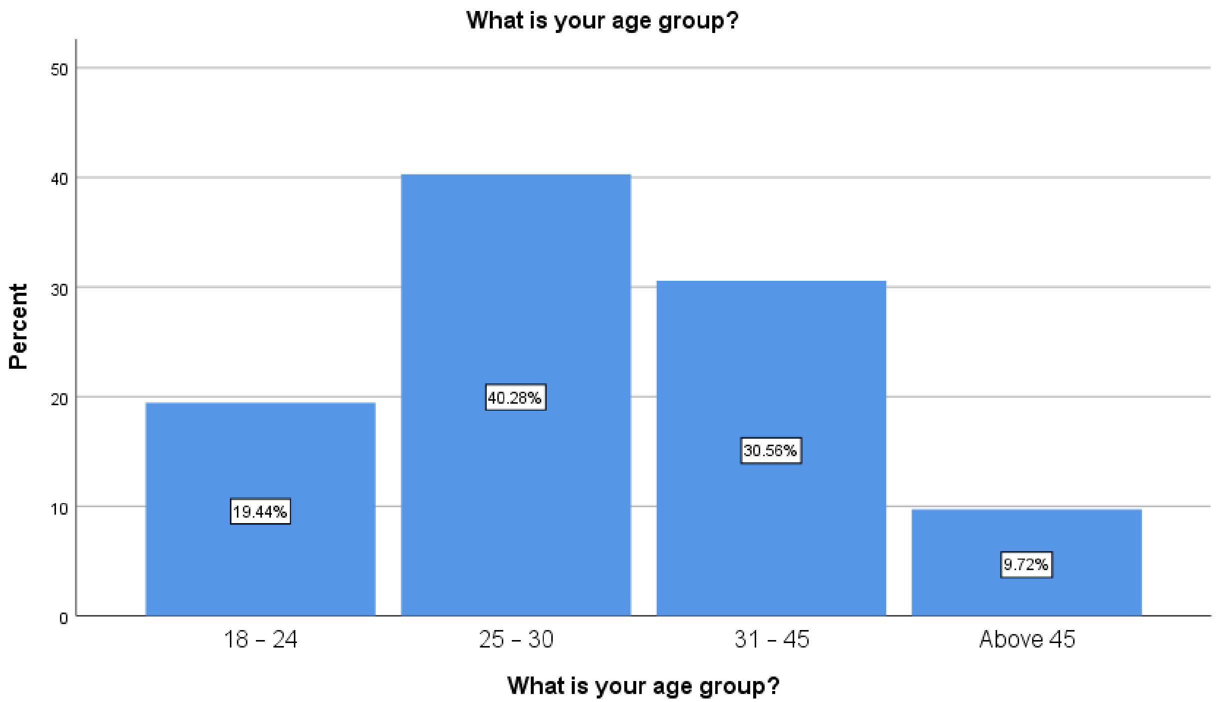
What improvements would inspire you to adopt AI-assisted MRI more confidently?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Better interpretability and explainability of AI decisions	18	25.0	25.0	25.0
	Stronger regulatory frameworks and standards	23	31.9	31.9	56.9
	More AI training for radiologists	24	33.3	33.3	90.3
	Reduced costs of implementation	7	9.7	9.7	100.0
	Total	72	100.0	100.0	

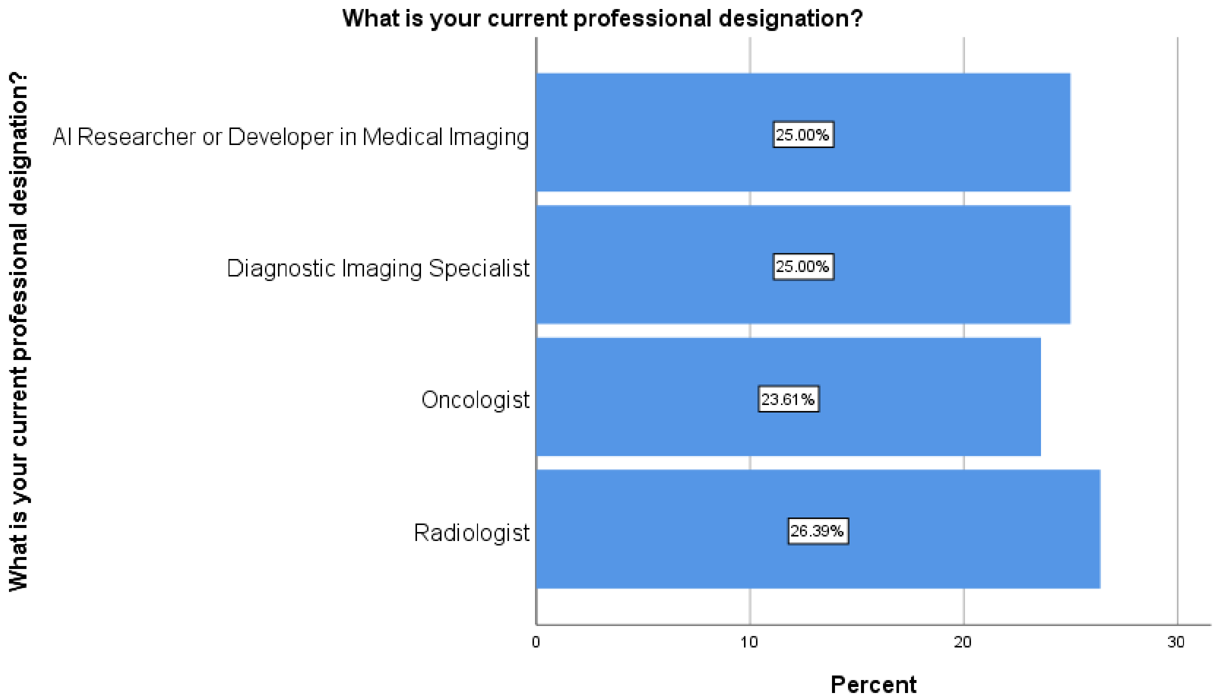
Do you believe AI-specific training programs can increase trust and adoption of AI-assisted MRI?

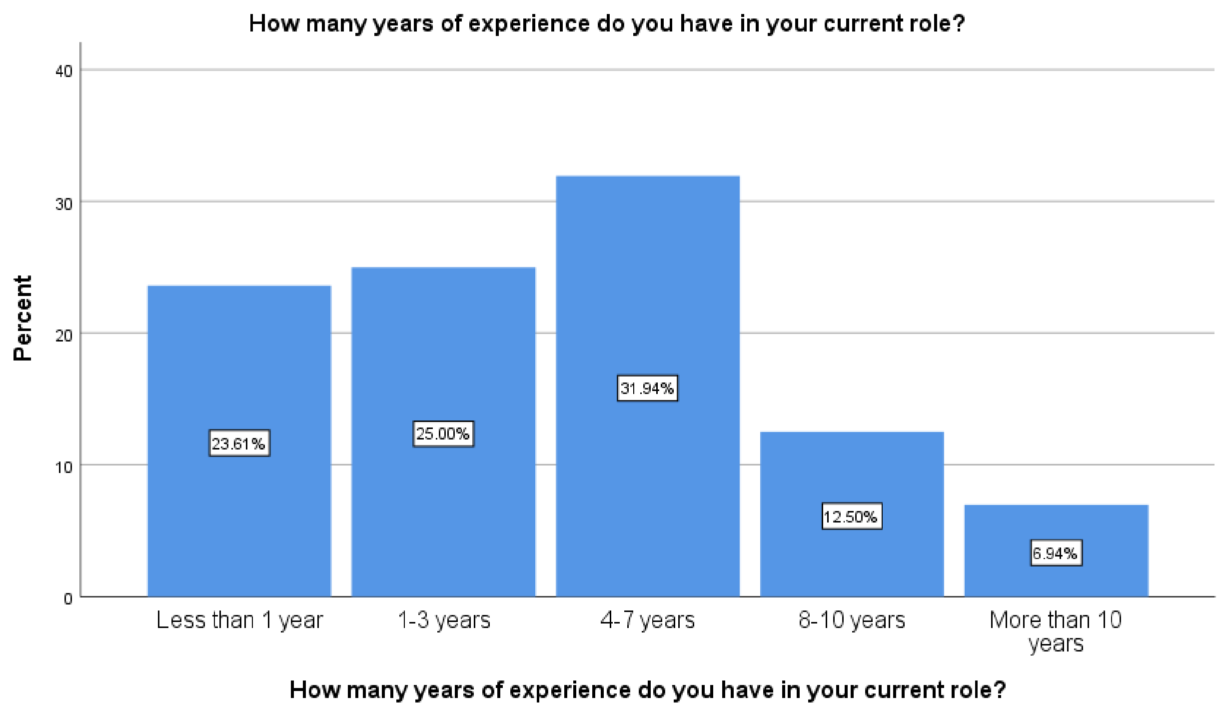
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree	13	18.1	18.1	18.1
	Agree	29	40.3	40.3	58.3
	Neutral	10	13.9	13.9	72.2
	Disagree	12	16.7	16.7	88.9
	Strongly Disagree	8	11.1	11.1	100.0
	Total	72	100.0	100.0	

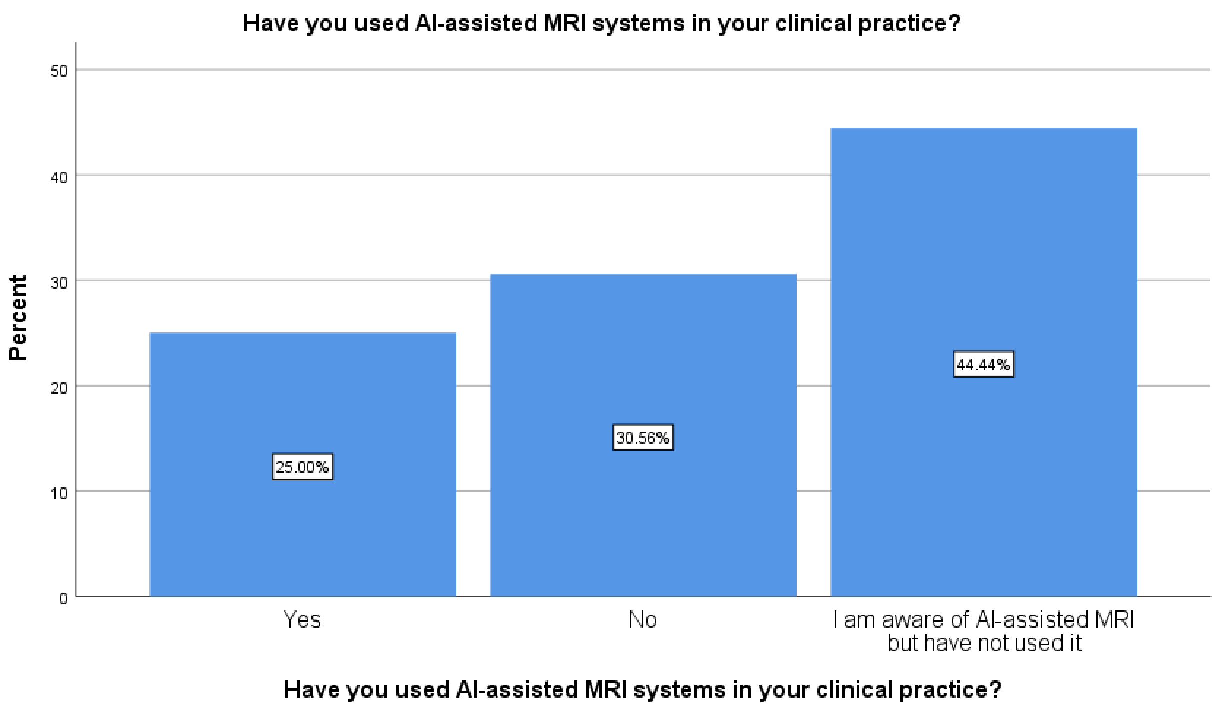
Bar Chart

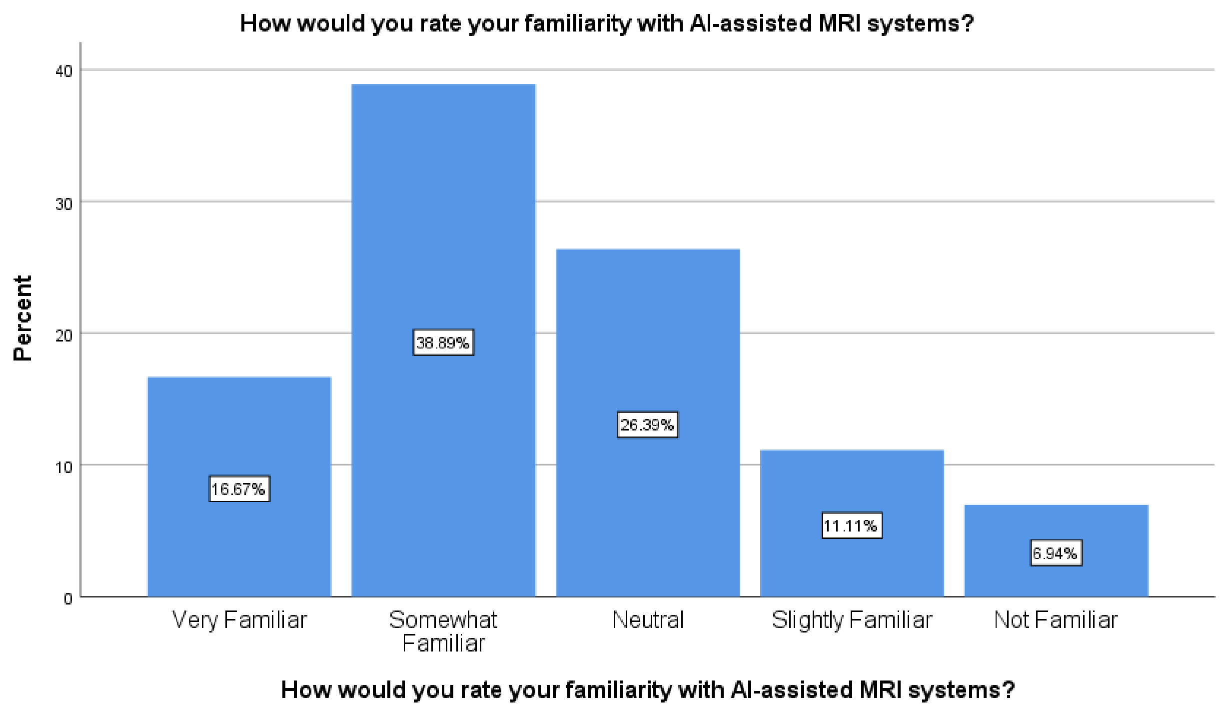


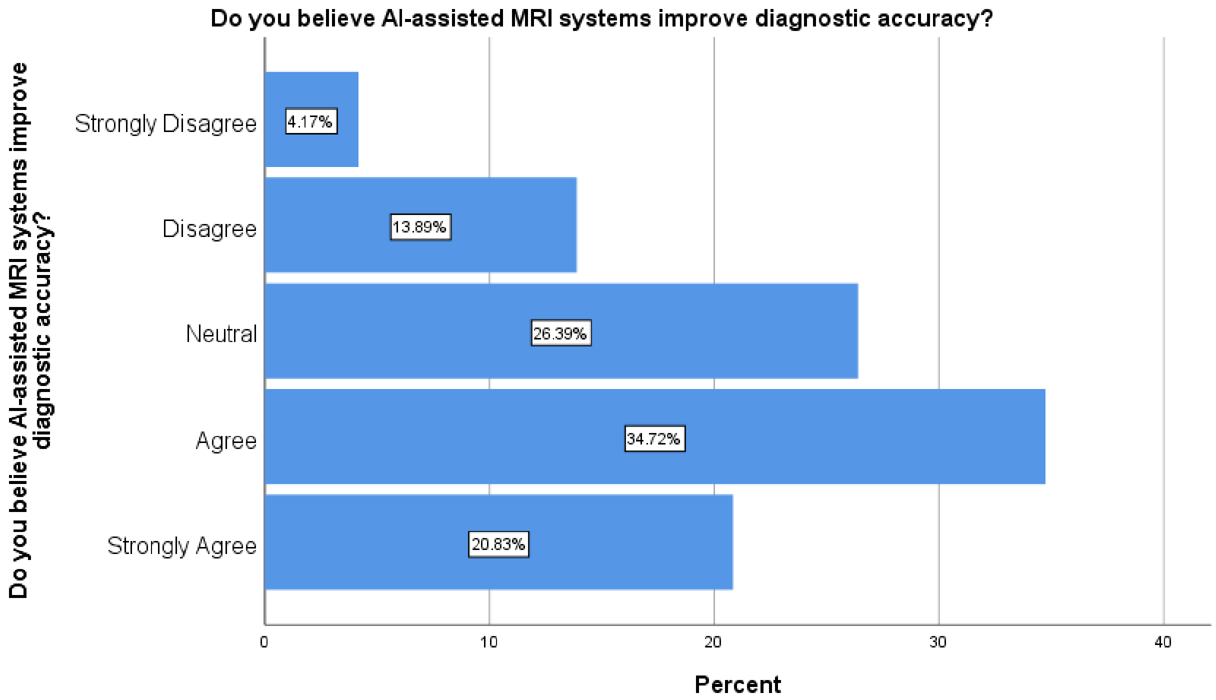
What is your age group?
Percent
50
40
30
20
10
0
19.44%
40.28%
30.56%
9.72%
18 – 24
25 – 30
31 – 45
Above 45
What is your age group?


What is your current professional designation?
What is your current professional designation?
AI Researcher or Developer in Medical Imaging
Diagnostic Imaging Specialist
Oncologist
Radiologist
25.00%
25.00%
23.61%
26.39%
0
10
20
30
Percent

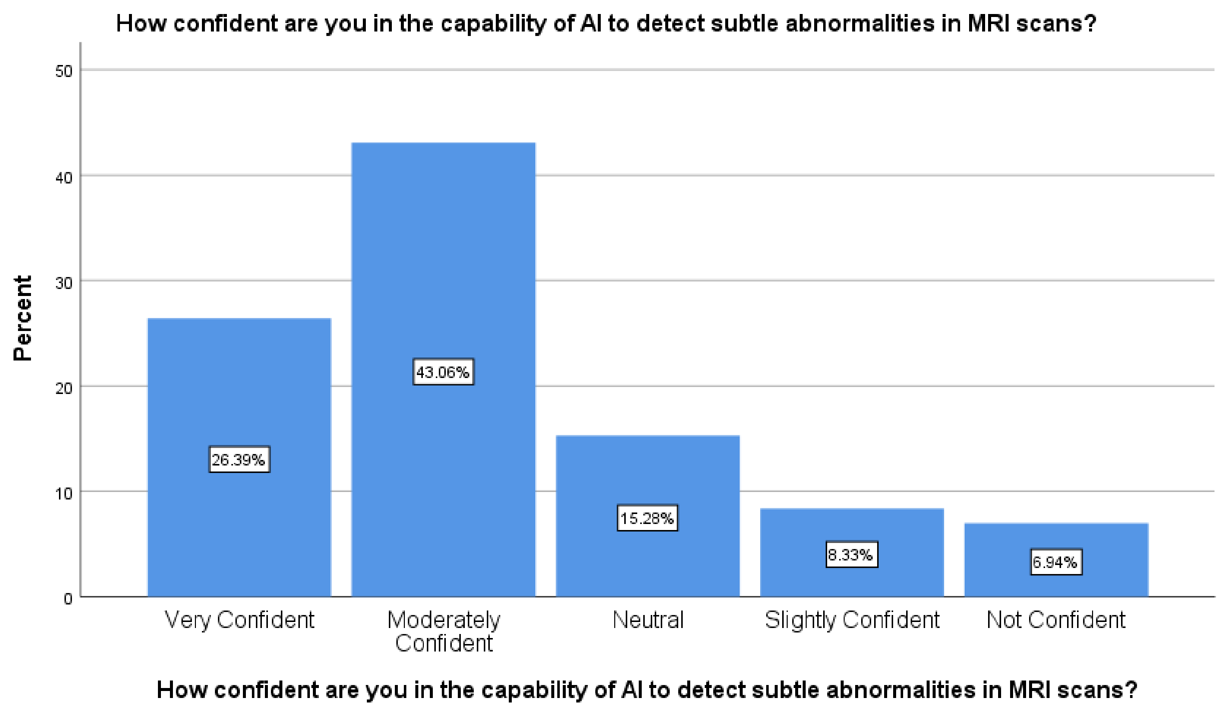

How many years of experience do you have in your current role?
Percent
40
30
20
10
0
23.61%
25.00%
31.94%
12.50%
6.94%
Less than 1 year
1-3 years
4-7 years
8-10 years
More than 10 years
How many years of experience do you have in your current role?

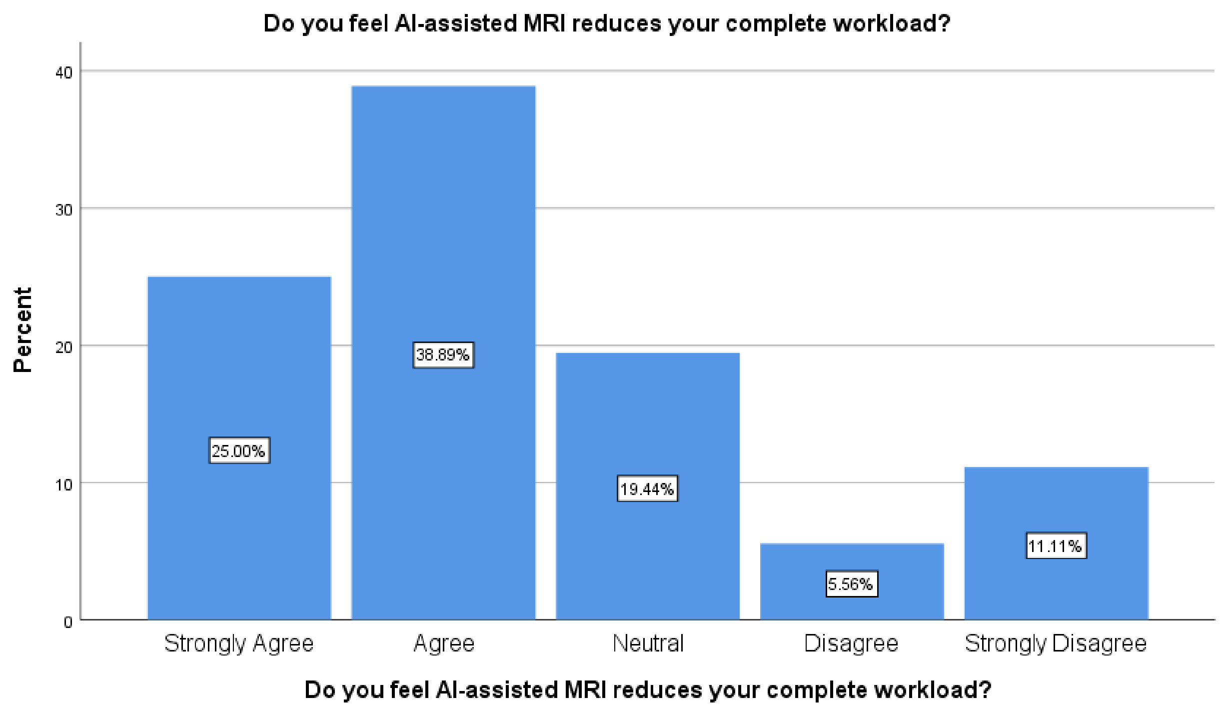

Have you used AI-assisted MRI systems in your clinical practice?
Percent
50
40
30
20
10
0
25.00%
30.56%
44.44%
Yes
No
I am aware of AI-assisted MRI but have not used it
Have you used AI-assisted MRI systems in your clinical practice?

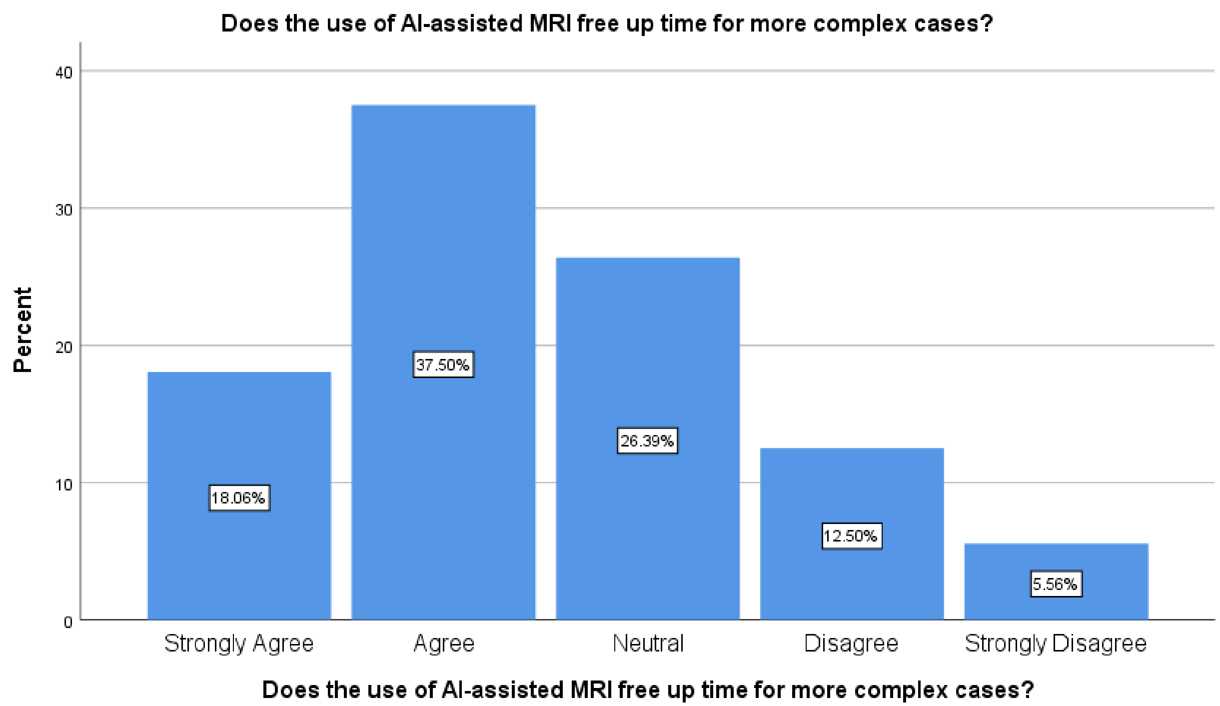

How would you rate your familiarity with AI-assisted MRI systems?
Percent
40
30
20
10
0
38.89%
26.39%
16.67%
11.11%
6.94%
Very Familiar
Somewhat Familiar
Neutral
Slightly Familiar
Not Familiar
How would you rate your familiarity with AI-assisted MRI systems?



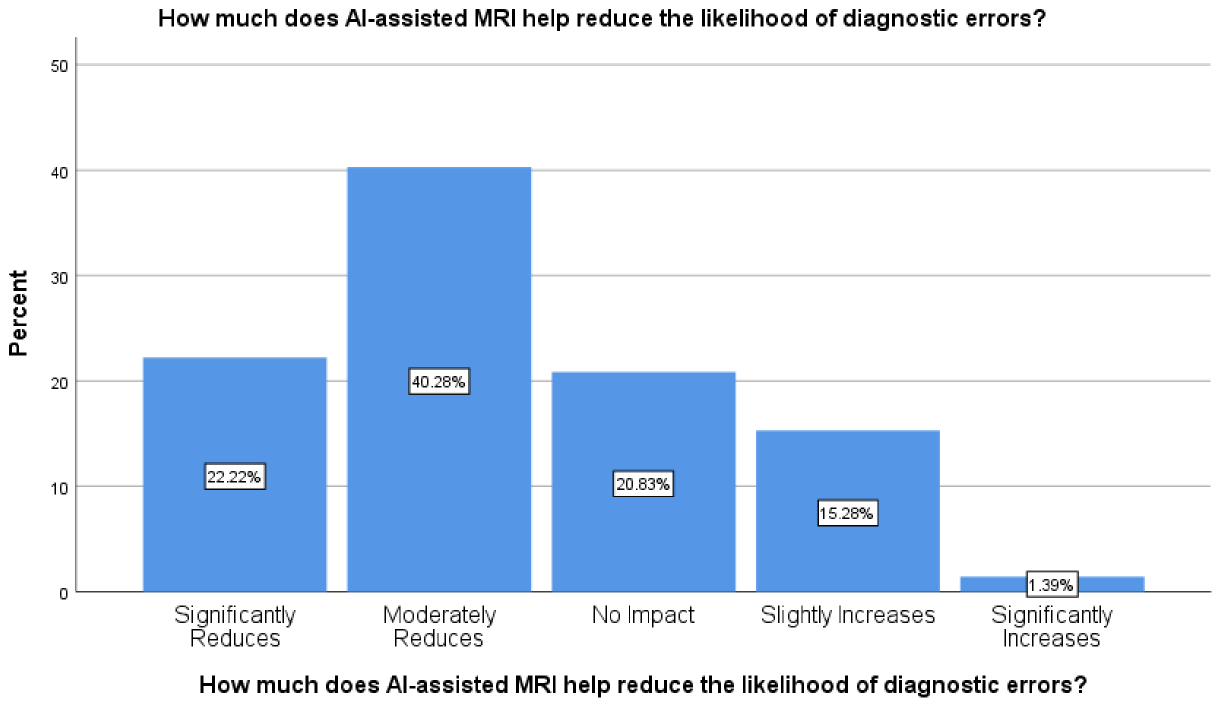
Do you believe AI-assisted MRI systems improve diagnostic accuracy?
Do you believe AI-assisted MRI systems improve diagnostic accuracy?
Strongly Disagree
4.17%
Disagree
13.89%
Neutral
26.39%
Agree
34.72%
Strongly Agree
20.83%
0
10
20
30
40
Percent

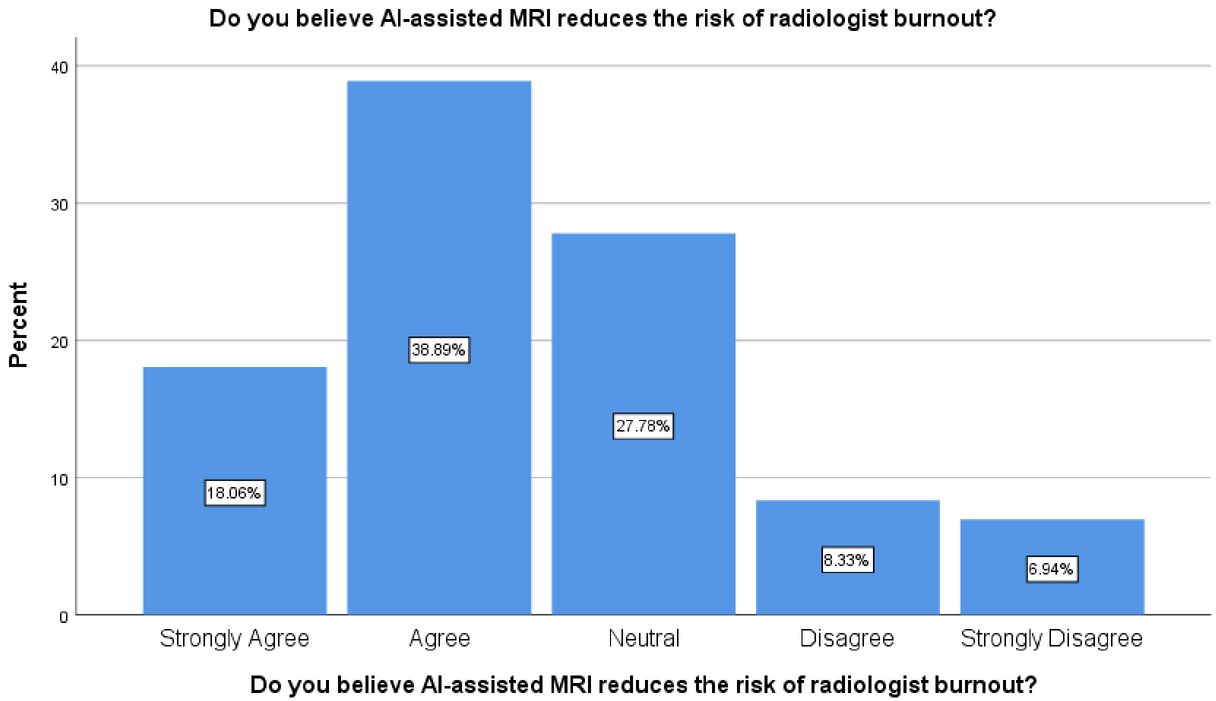

How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?
Percent
50
40
30
20
10
0
26.39%
43.06%
15.28%
8.33%
6.94%
Very Confident
Moderately Confident
Neutral
Slightly Confident
Not Confident
How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?

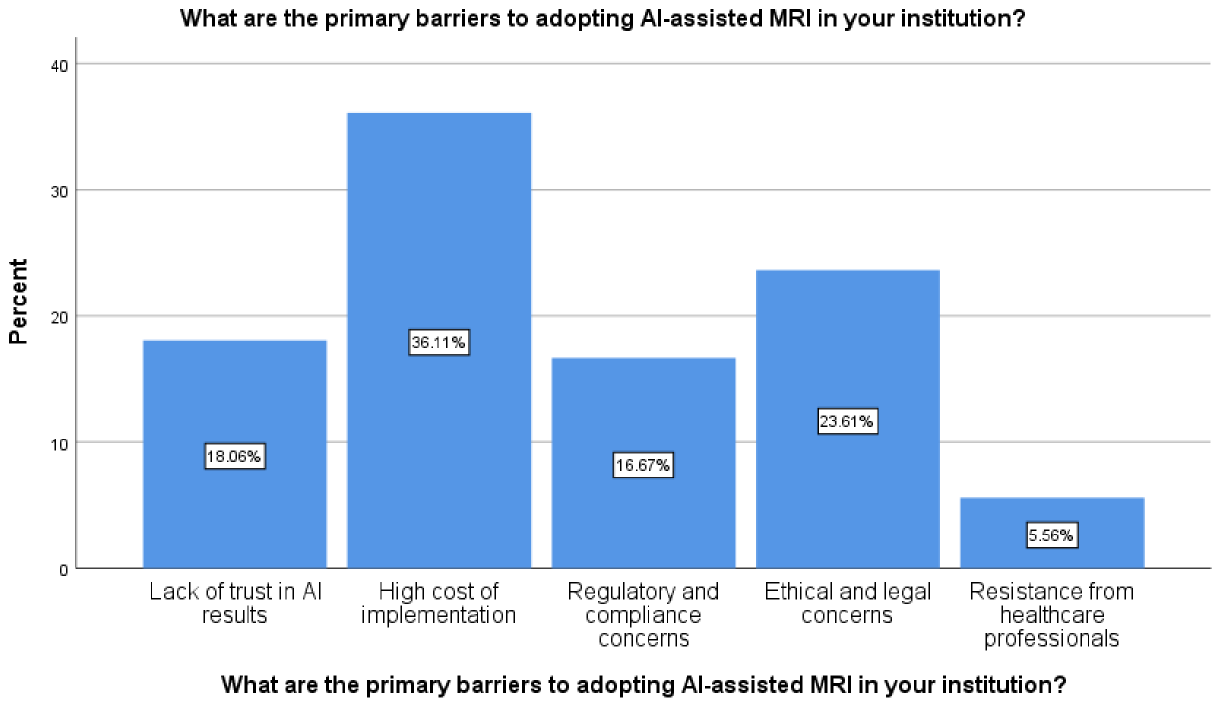

Do you feel AI-assisted MRI reduces your complete workload?
Percent
40
30
20
10
0
25.00%
38.89%
19.44%
5.56%
11.11%
Strongly Agree
Agree
Neutral
Disagree
Strongly Disagree
Do you feel AI-assisted MRI reduces your complete workload?



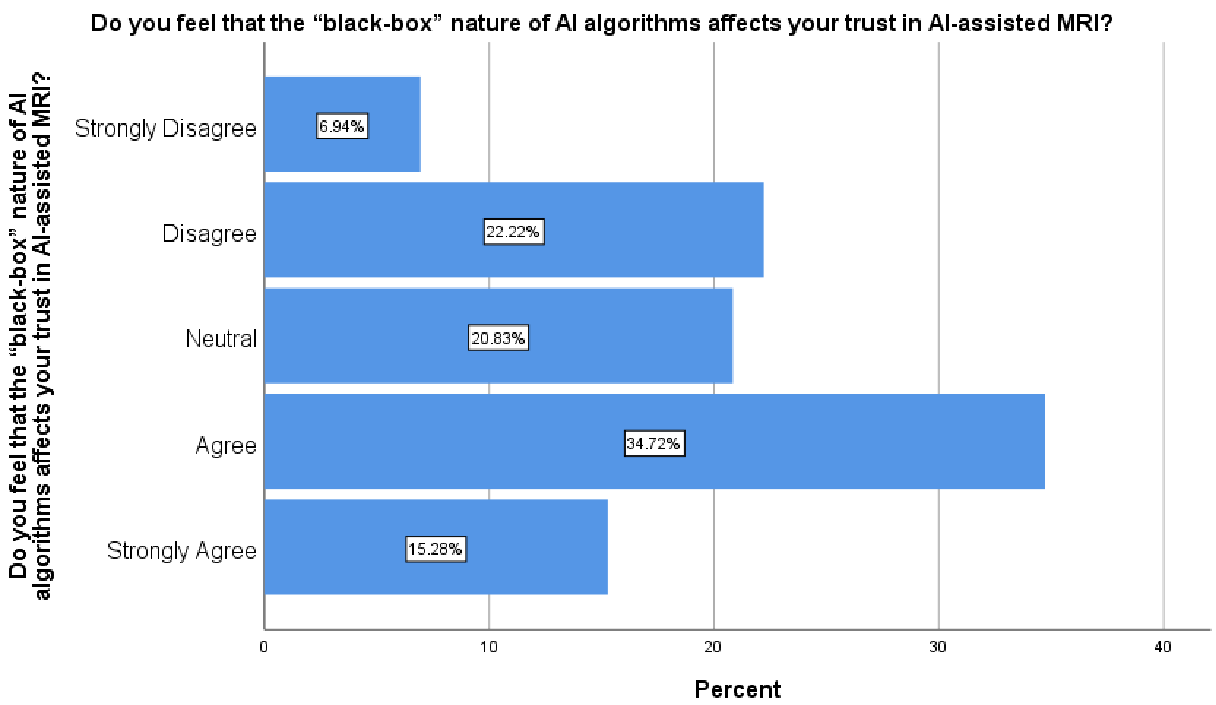
Does the use of AI-assisted MRI free up time for more complex cases?
Percent
40
30
20
10
0
18.06%
37.50%
26.39%
12.50%
5.56%
Strongly Agree
Agree
Neutral
Disagree
Strongly Disagree
Does the use of AI-assisted MRI free up time for more complex cases?


How much does AI-assisted MRI help reduce the likelihood of diagnostic errors?
Percent
50
40
30
20
10
0
22.22%
40.28%
20.83%
15.28%
1.39%
Significantly Reduces
Moderately Reduces
No Impact
Slightly Increases
Significantly Increases
How much does AI-assisted MRI help reduce the likelihood of diagnostic errors?

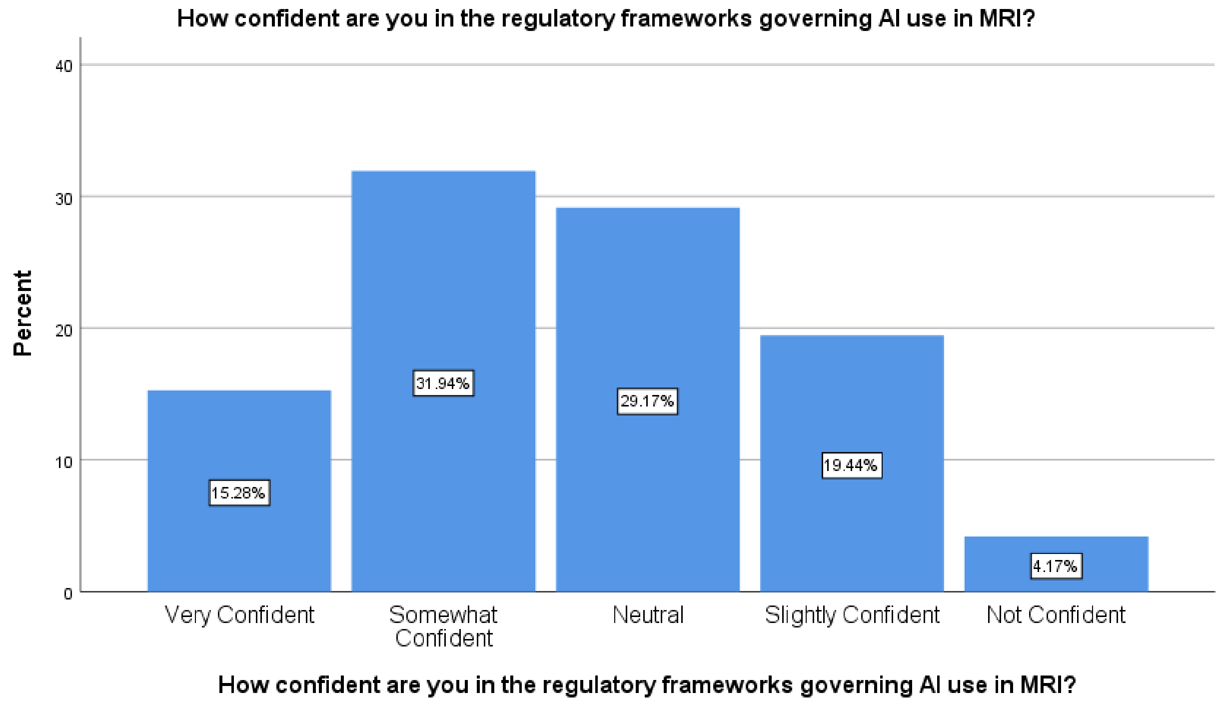

Do you believe AI-assisted MRI reduces the risk of radiologist burnout?
Percent
40
30
20
10
0
18.06%
38.89%
27.78%
8.33%
6.94%
Strongly Agree
Agree
Neutral
Disagree
Strongly Disagree
Do you believe AI-assisted MRI reduces the risk of radiologist burnout?

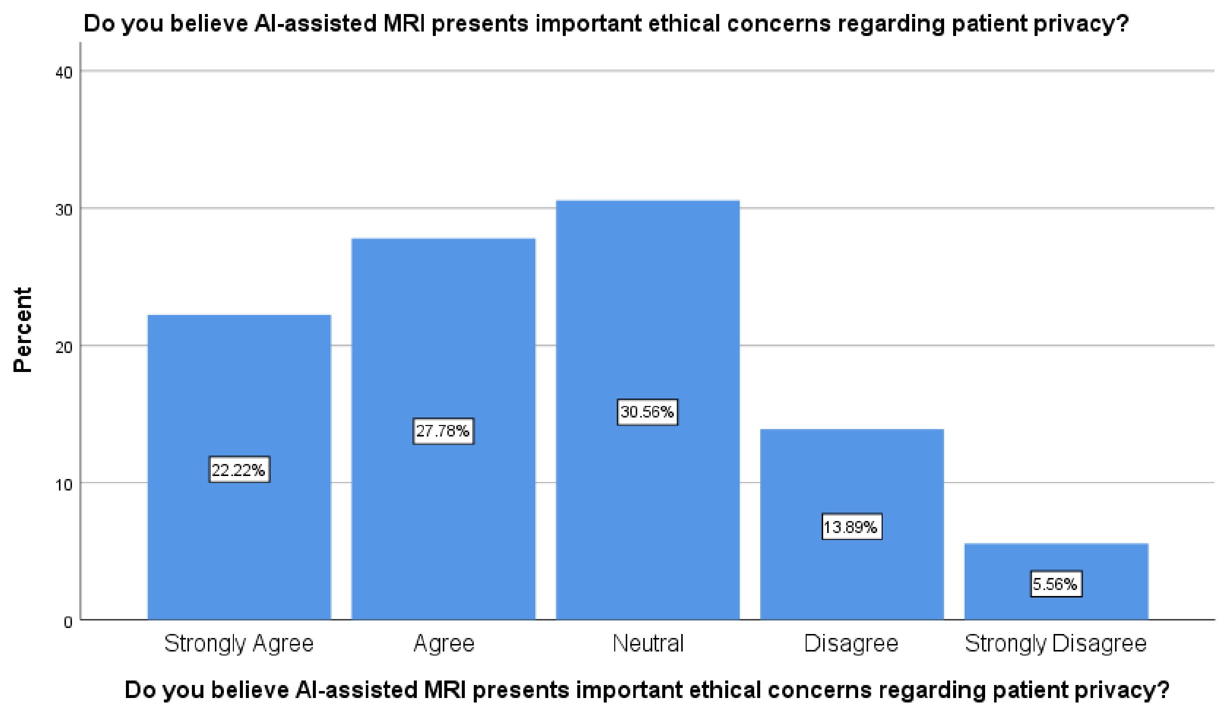


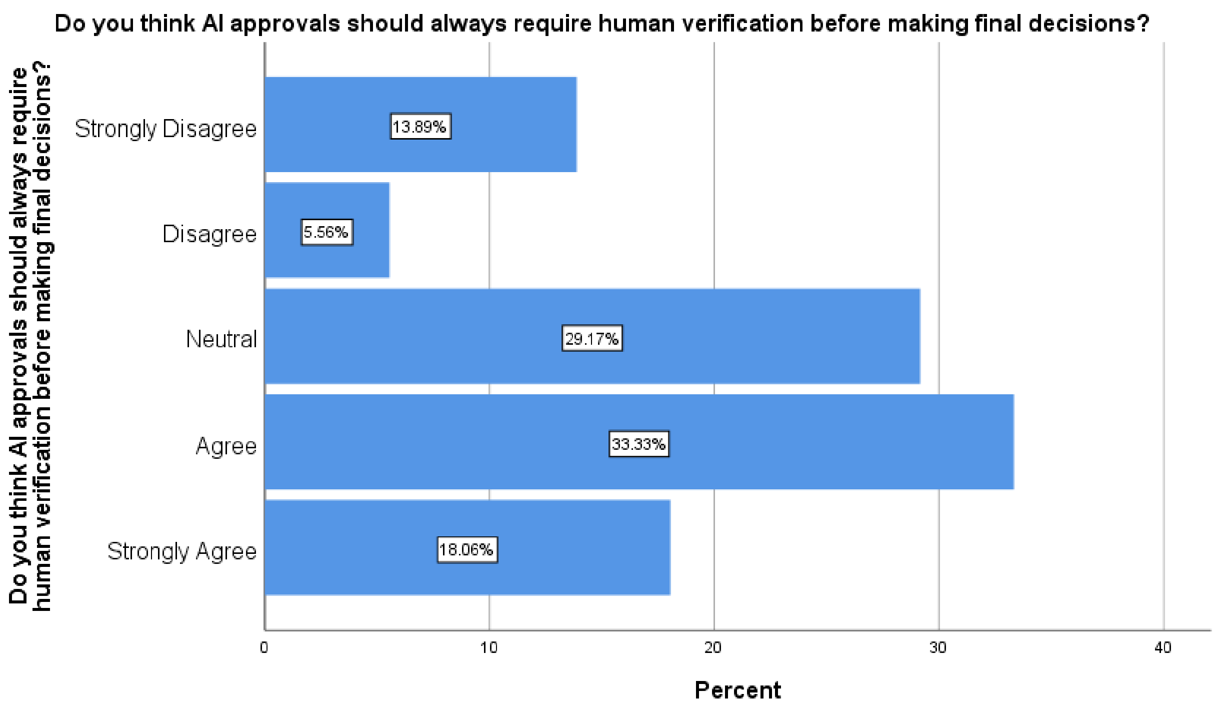
What are the primary barriers to adopting AI-assisted MRI in your institution?
Percent
0
10
20
30
40
18.06%
36.11%
16.67%
23.61%
5.56%
Lack of trust in AI results
High cost of implementation
Regulatory and compliance concerns
Ethical and legal concerns
Resistance from healthcare professionals
What are the primary barriers to adopting AI-assisted MRI in your institution?



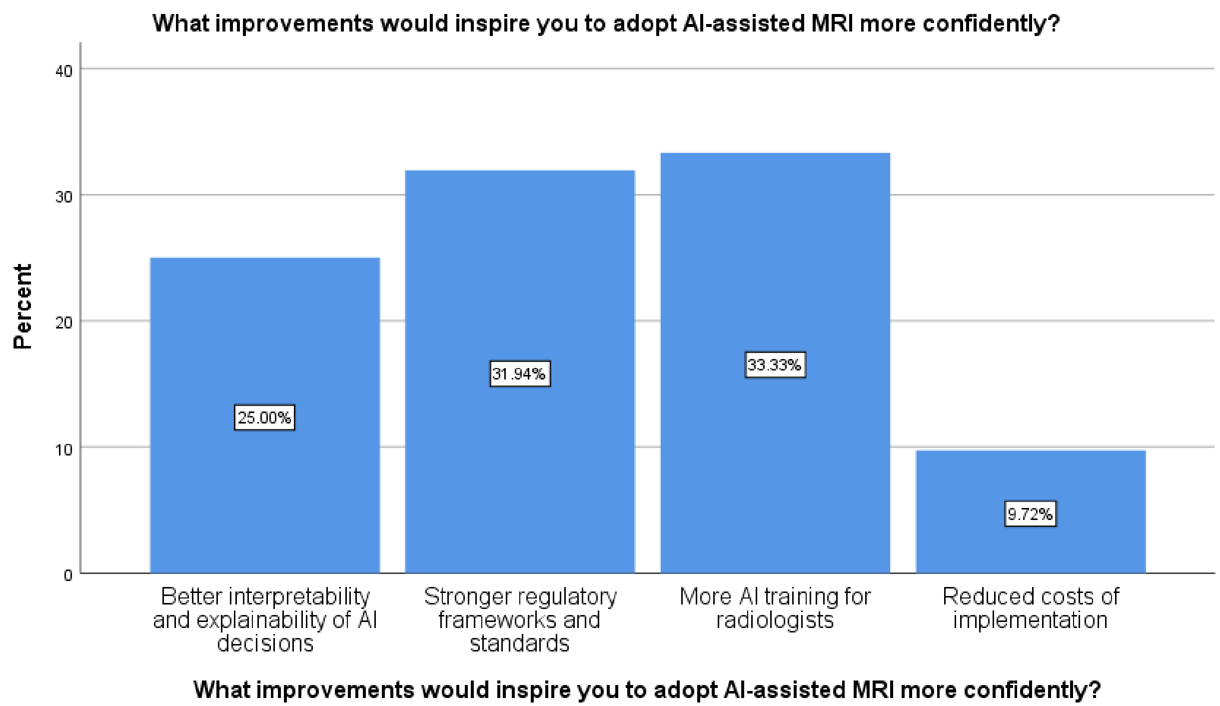
Do you feel that the “black-box” nature of AI algorithms affects your trust in AI-assisted MRI?
Do you feel that the “black-box” nature of AI algorithms affects your trust in AI-assisted MRI?
Strongly Disagree
6.94%
Disagree
22.22%
Neutral
20.83%
Agree
34.72%
Strongly Agree
15.28%
0
10
20
30
40
Percent

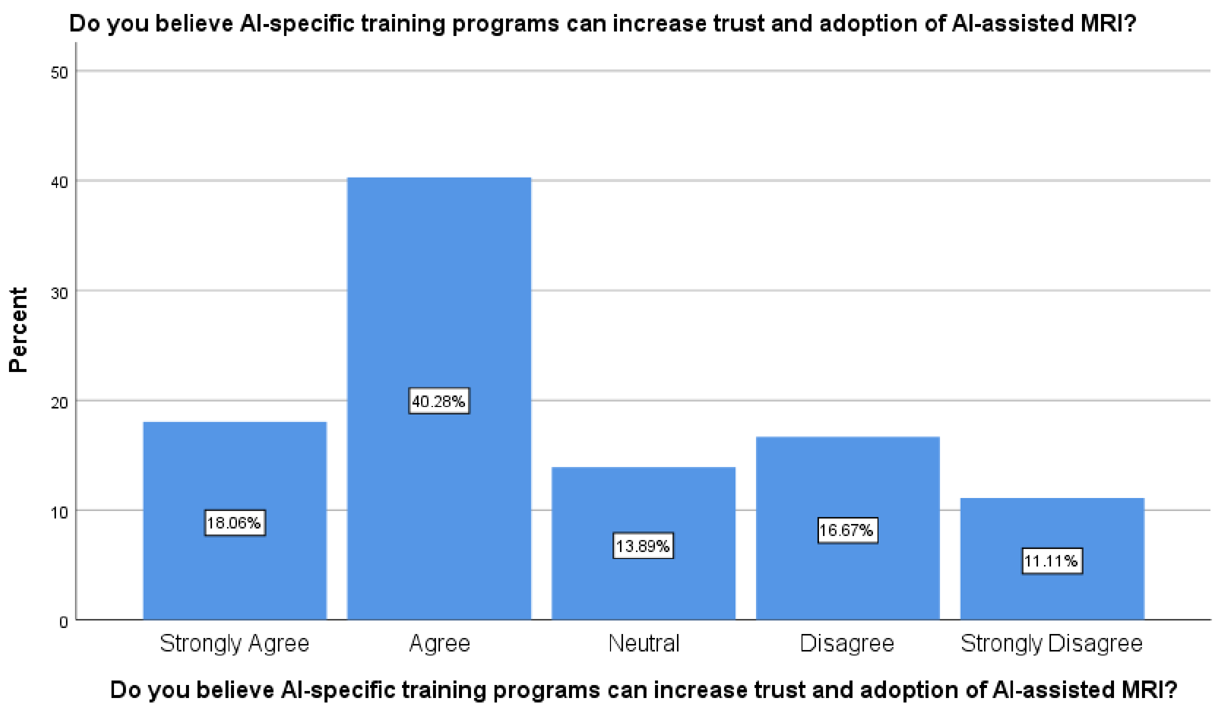

How confident are you in the regulatory frameworks governing AI use in MRI?
Percent
40
30
20
10
0
31.94%
29.17%
19.44%
15.28%
4.17%
Very Confident
Somewhat Confident
Neutral
Slightly Confident
Not Confident
How confident are you in the regulatory frameworks governing AI use in MRI?


Do you believe AI-assisted MRI presents important ethical concerns regarding patient privacy?
Percent
40
30
20
10
0
22.22%
27.78%
30.56%
13.89%
5.56%
Strongly Agree
Agree
Neutral
Disagree
Strongly Disagree
Do you believe AI-assisted MRI presents important ethical concerns regarding patient privacy?



Do you think AI approvals should always require human verification before making final decisions?
Do you think AI approvals should always require human verification before making final decisions?
Strongly Disagree
Disagree
Neutral
Agree
Strongly Agree
13.89%
5.56%
29.17%
33.33%
18.06%
0
10
20
30
40
Percent


What improvements would inspire you to adopt AI-assisted MRI more confidently?
Percent
40
30
20
10
0
25.00%
31.94%
33.33%
9.72%
Better interpretability and explainability of AI decisions
Stronger regulatory frameworks and standards
More AI training for radiologists
Reduced costs of implementation
What improvements would inspire you to adopt AI-assisted MRI more confidently?


Do you believe AI-specific training programs can increase trust and adoption of AI-assisted MRI?
Percent
50
40
30
20
10
0
18.06%
40.28%
13.89%
16.67%
11.11%
Strongly Agree
Agree
Neutral
Disagree
Strongly Disagree
Do you believe AI-specific training programs can increase trust and adoption of AI-assisted MRI?

Correlation Analysis

Descriptive Statistics

	Mean	Std. Deviation	N
How would you rate your familiarity with AI-assisted MRI systems?	2.53	1.113	72
Do you believe AI-assisted MRI systems improve diagnostic accuracy?	2.46	1.100	72

Correlations

		How would you rate your familiarity with AI-assisted MRI systems?	Do you believe AI-assisted MRI systems improve diagnostic accuracy?
How would you rate your familiarity with AI-assisted MRI systems?	Pearson Correlation	1	.375**
	Sig. (2-tailed)		.001
	Sum of Squares and Cross-products	87.944	32.583
	Covariance	1.239	.459
	N	72	72
	Pearson Correlation	.375**	1
	Sig. (2-tailed)	.001	

Do you believe AI-assisted MRI systems improve diagnostic accuracy?	Sum of Squares and Cross-products	32.583	85.875
	Covariance	.459	1.210
	N	72	72

**. Correlation is significant at the 0.01 level (2-tailed).

One Way ANOVA

Descriptives

How would you rate your familiarity with AI-assisted MRI systems?

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
						Lower Bound	Upper Bound			
18 – 24		14	2.29	.994	.266	1.71	2.86	1	4	
25 – 30		29	2.41	1.086	.202	2.00	2.83	1	5	
31 – 45		22	2.77	1.152	.246	2.26	3.28	1	5	
Above 45		7	2.71	1.380	.522	1.44	3.99	1	5	
Total		72	2.53	1.113	.131	2.27	2.79	1	5	
Model	Fixed Effects			1.119	.132	2.26	2.79			
	Random Effects				.132[a]	2.11[a]	2.95[a]			-.02

a. Warning: Between-component variance is negative. It was replaced by 0.0 in computing this random effects measure.

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
Based on Mean	.379	3	68	.768
Based on Median	.341	3	68	.796

How would you rate your familiarity with AI-assisted MRI systems?	Based on Median and with adjusted df	.341	3	55.179	.796
	Based on trimmed mean	.399	3	68	.754

ANOVA

How would you rate your familiarity with AI-assisted MRI systems?

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.761	3	.920	.735	.535
Within Groups	85.184	68	1.253		
Total	87.944	71			

Robust Tests of Equality of Means

How would you rate your familiarity with AI-assisted MRI systems?

	Statistic[a]	df1	df2	Sig.
Welch	.702	3	21.954	.561
Brown-Forsythe	.666	3	28.607	.580

a. Asymptotically F distributed.

Post Hoc Tests

Multiple Comparisons

Dependent Variable: How would you rate your familiarity with AI-assisted MRI systems?

Tukey HSD

(I) What is your age group?	(J) What is your age group?	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
18 – 24	25 – 30	-.128	.364	.985	-1.09	.83
	31 – 45	-.487	.383	.583	-1.49	.52
	Above 45	-.429	.518	.841	-1.79	.94
25 – 30	18 – 24	.128	.364	.985	-.83	1.09
	31 – 45	-.359	.316	.670	-1.19	.47
	Above 45	-.300	.471	.919	-1.54	.94
31 – 45	18 – 24	.487	.383	.583	-.52	1.49
	25 – 30	.359	.316	.670	-.47	1.19
	Above 45	.058	.486	.999	-1.22	1.34
Above 45	18 – 24	.429	.518	.841	-.94	1.79
	25 – 30	.300	.471	.919	-.94	1.54
	31 – 45	-.058	.486	.999	-1.34	1.22

Homogeneous Subsets

How would you rate your familiarity with AI-assisted MRI systems?

Tukey HSD[a,b]

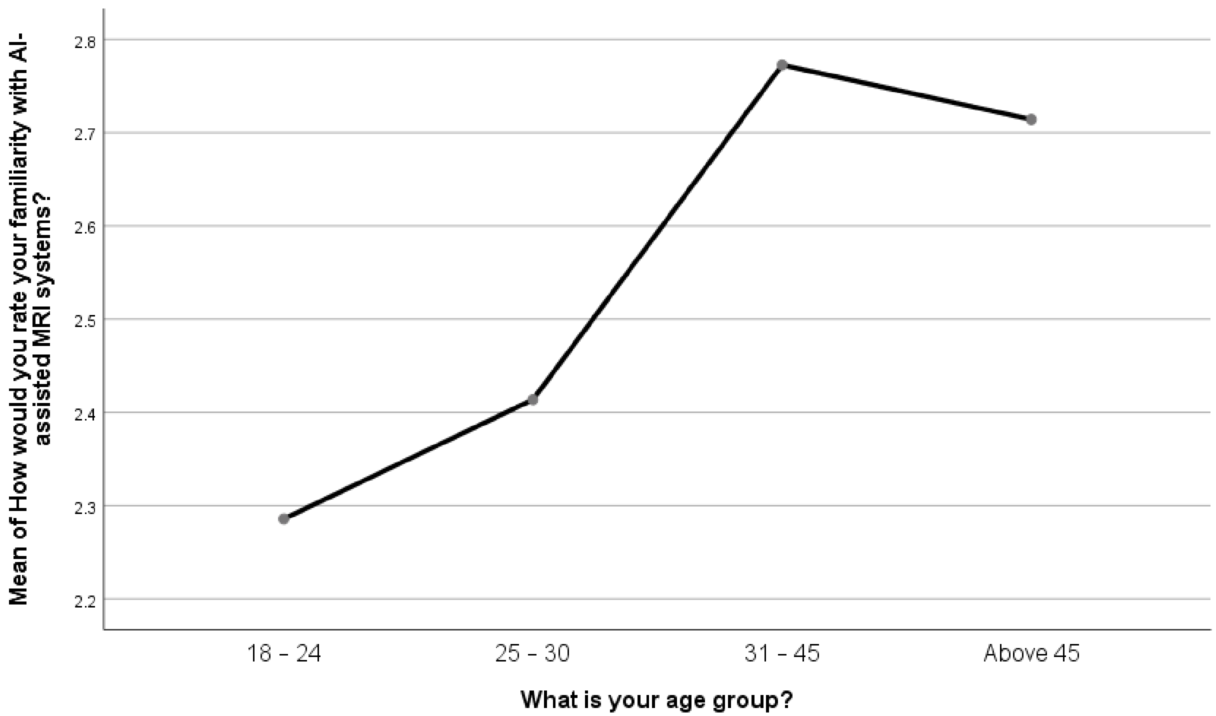
What is your age group?	N	Subset for alpha = 0.05 1

18 – 24	14	2.29
25 – 30	29	2.41
Above 45	7	2.71
31 – 45	22	2.77
Sig.		.670

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 13.595.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.



Chi-Square

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Have you used AI-assisted MRI systems in your clinical practice? * What are the primary barriers to adopting AI-assisted MRI in your institution?	72	100.0%	0	0.0%	72	100.0%

Have you used AI-assisted MRI systems in your clinical practice? * What are the primary barriers to adopting AI-assisted MRI in your institution? Crosstabulation

			What are the primary barriers to adopting AI-assisted MRI in your institution?					
			Lack of trust in AI results	High cost of implementation	Regulatory and compliance concerns	Ethical and legal concerns	Resistance from healthcare professionals	Total
Have you used AI-assisted MRI systems	Yes	Count	5	5	3	4	1	18
		Expected Count	3.3	6.5	3.0	4.3	1.0	18.0

in your clinical practice?		% within What are the primary barriers to adopting AI-assisted MRI in your institution?	38.5%	19.2%	25.0%	23.5%	25.0%	25.0%
	No	Count	4	6	6	5	1	22
		Expected Count	4.0	7.9	3.7	5.2	1.2	22.0
		% within What are the primary barriers to adopting AI-assisted MRI in your institution?	30.8%	23.1%	50.0%	29.4%	25.0%	30.6%
	I am aware of AI-assisted MRI but have not used it	Count	4	15	3	8	2	32
		Expected Count	5.8	11.6	5.3	7.6	1.8	32.0
		% within What are the primary barriers to adopting AI-assisted MRI in your institution?	30.8%	57.7%	25.0%	47.1%	50.0%	44.4%
Total		Count	13	26	12	17	4	72
		Expected Count	13.0	26.0	12.0	17.0	4.0	72.0
		% within What are the primary barriers to adopting AI-assisted MRI in your institution?	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)

Pearson Chi-Square	5.960[a]	8	.652
Likelihood Ratio	5.831	8	.666
Linear-by-Linear Association	.157	1	.692
N of Valid Cases	72		

a. 8 cells (53.3%) have expected count less than 5. The minimum expected count is 1.00.

Directional Measures

			Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Nominal by Nominal	Lambda	Symmetric	.047	.070	.651	.515
		Have you used AI-assisted MRI systems in your clinical practice? Dependent	.100	.101	.949	.343
		What are the primary barriers to adopting AI-assisted MRI in your institution? Dependent	.000	.069	.000	1.000
	Goodman and Kruskal tau	Have you used AI-assisted MRI systems in your clinical practice? Dependent	.045	.037		.596[c]
		What are the primary barriers to adopting AI-assisted MRI in your institution? Dependent	.025	.022		.515[c]
	Uncertainty Coefficient	Symmetric	.032	.026	1.216	.666[d]

		Have you used AI-assisted MRI systems in your clinical practice? Dependent	.038	.031	1.216	.666[d]
		What are the primary barriers to adopting AI-assisted MRI in your institution? Dependent	.027	.023	1.216	.666[d]
Ordinal by Ordinal	Somers' d	Symmetric	.037	.105	.353	.724
		Have you used AI-assisted MRI systems in your clinical practice? Dependent	.034	.098	.353	.724
		What are the primary barriers to adopting AI-assisted MRI in your institution? Dependent	.040	.113	.353	.724

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on chi-square approximation

d. Likelihood ratio chi-square probability.

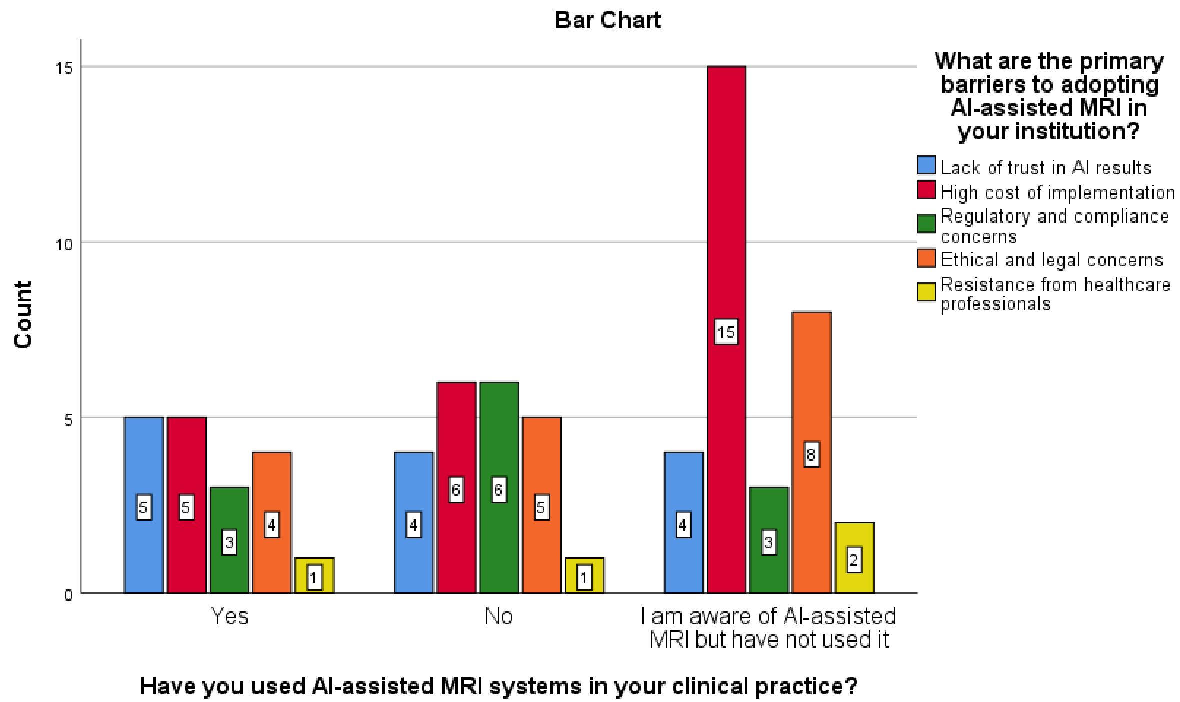
Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Nominal by Nominal	Phi	.288			.652
	Cramer's V	.203			.652
	Contingency Coefficient	.277			.652
Ordinal by Ordinal	Kendall's tau-b	.037	.105	.353	.724
	Kendall's tau-c	.039	.110	.353	.724

Gamma	.052	.148	.353	.724
N of Valid Cases	72			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.



T-Test

Group Statistics

	Have you used AI-assisted MRI systems in your clinical practice?	N	Mean	Std. Deviation	Std. Error Mean
Do you believe AI-assisted MRI systems improve diagnostic accuracy?	Yes	18	2.33	1.283	.302
	No	22	2.23	.869	.185

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Do you believe AI-assisted MRI systems improve diagnostic accuracy?	Equal variances assumed	3.996	.053	.311	38	.758	.106	.341	-.585	.797
	Equal variances not assumed			.299	28.862	.767	.106	.355	-.620	.832

Regression

Descriptive Statistics

	Mean	Std. Deviation	N
Do you believe AI-assisted MRI systems improve diagnostic accuracy?	2.46	1.100	72
How would you rate your familiarity with AI-assisted MRI systems?	2.53	1.113	72
How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?	2.26	1.151	72
How confident are you in the regulatory frameworks governing AI use in MRI?	2.65	1.090	72

Correlations

		Do you believe AI-assisted MRI systems improve diagnostic accuracy?	How would you rate your familiarity with AI-assisted MRI systems?	How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?	How confident are you in the regulatory frameworks governing AI use in MRI?
Pearson Correlation	Do you believe AI-assisted MRI systems improve diagnostic accuracy?	1.000	.375	.192	.099

	How would you rate your familiarity with AI-assisted MRI systems?	.375	1.000	.110	.165
	How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?	.192	.110	1.000	.288
	How confident are you in the regulatory frameworks governing AI use in MRI?	.099	.165	.288	1.000
Sig. (1-tailed)	Do you believe AI-assisted MRI systems improve diagnostic accuracy?	.	.001	.053	.203
	How would you rate your familiarity with AI-assisted MRI systems?	.001	.	.180	.083
	How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?	.053	.180	.	.007
	How confident are you in the regulatory frameworks governing AI use in MRI?	.203	.083	.007	.
N	Do you believe AI-assisted MRI systems improve diagnostic accuracy?	72	72	72	72
	How would you rate your familiarity with AI-assisted MRI systems?	72	72	72	72

	How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?	72	72	72	72
	How confident are you in the regulatory frameworks governing AI use in MRI?	72	72	72	72

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	How confident are you in the regulatory frameworks governing AI use in MRI?, How would you rate your familiarity with AI-assisted MRI systems?, How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?[b]	.	Enter

a. Dependent Variable: Do you believe AI-assisted MRI systems improve diagnostic accuracy?
b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.405[a]	.164	.127	1.028	.164	4.439	3	68	.007

a. Predictors: (Constant), How confident are you in the regulatory frameworks governing AI use in MRI?, How would you rate your familiarity with AI-assisted MRI systems?, How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?
b. Dependent Variable: Do you believe AI-assisted MRI systems improve diagnostic accuracy?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14.064	3	4.688	4.439	.007[b]
	Residual	71.811	68	1.056		
	Total	85.875	71			

a. Dependent Variable: Do you believe AI-assisted MRI systems improve diagnostic accuracy?
b. Predictors: (Constant), How confident are you in the regulatory frameworks governing AI use in MRI?, How would you rate your familiarity with AI-assisted MRI systems?, How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Z
		B	Std. Error	Beta			Lower Bound	Upper Bound	
1	(Constant)	1.239	.422		2.940	.004	.398	2.081	
	How would you rate your familiarity with AI-assisted MRI systems?	.354	.111	.359	3.183	.002	.132	.577	
	How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?	.147	.111	.154	1.330	.188	-.074	.369	
	How confident are you in the regulatory frameworks governing AI use in MRI?	-.004	.118	-.004	-.035	.972	-.240	.231	

a. Dependent Variable: Do you believe AI-assisted MRI systems improve diagnostic accuracy?

Collinearity Diagnostics[a]

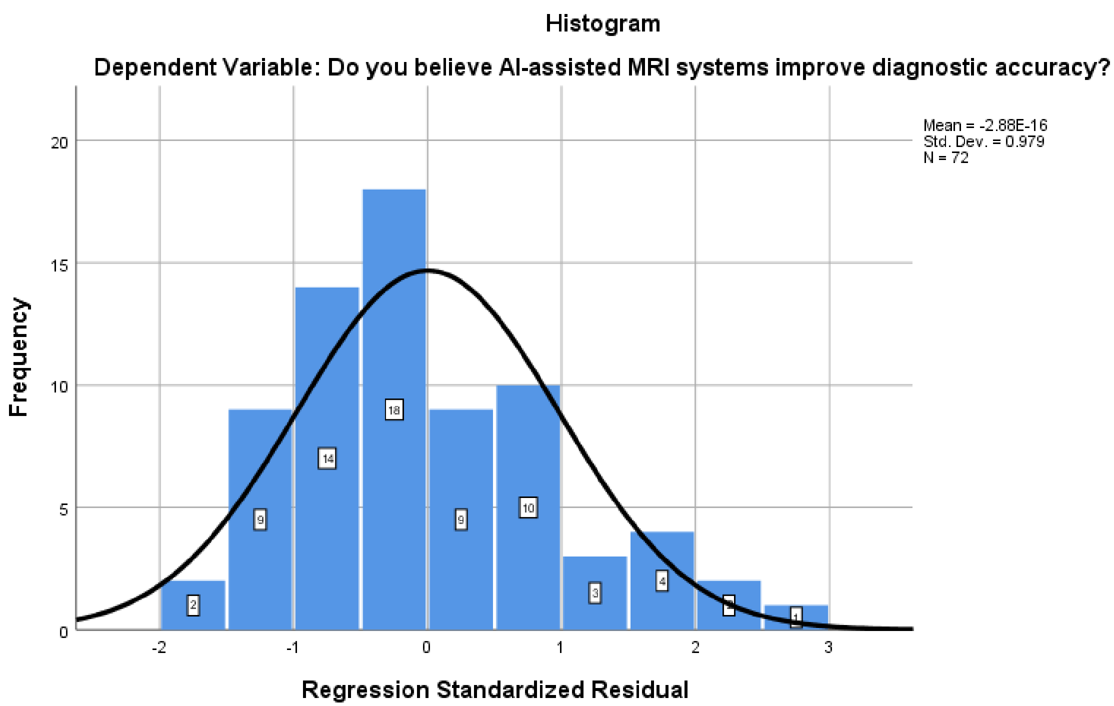
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	How would you rate your familiarity with AI-assisted MRI systems?	How confident are you in the capability of AI to detect subtle abnormalities in MRI scans?	How confident are you in the regulatory frameworks governing AI use in MRI?
1	1	3.661	1.000	.01	.01	.01	.01
	2	.164	4.720	.01	.41	.62	.00
	3	.114	5.669	.01	.28	.31	.67
	4	.060	7.797	.98	.30	.06	.32

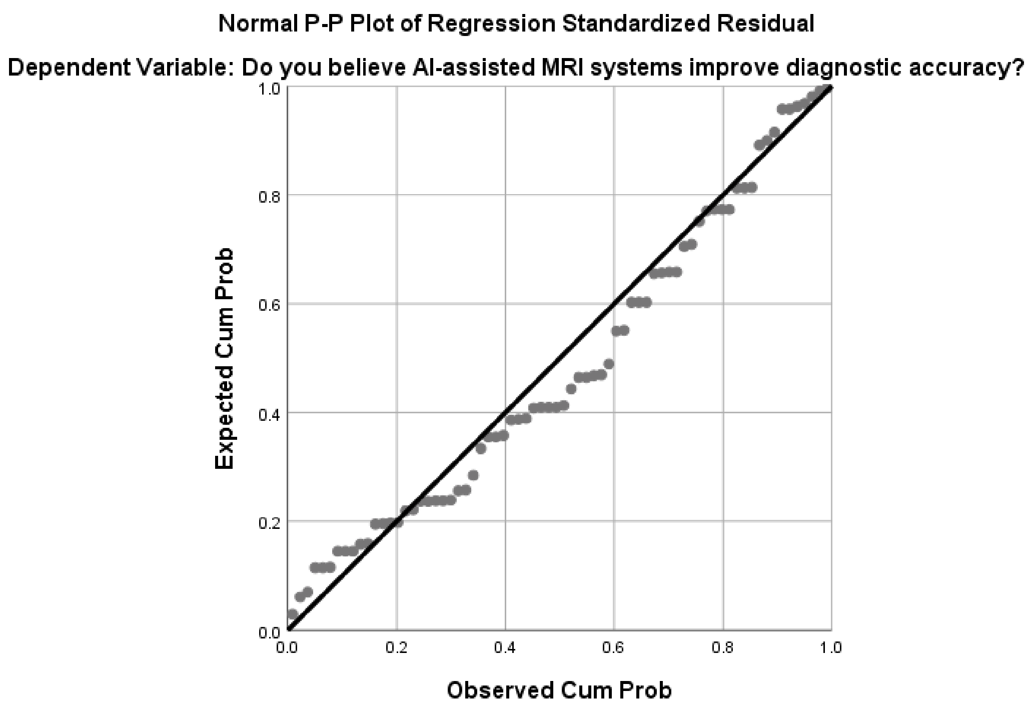
a. Dependent Variable: Do you believe AI-assisted MRI systems improve diagnostic accuracy?

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.73	3.30	2.46	.445	72
Residual	-1.944	2.761	.000	1.006	72
Std. Predicted Value	-1.639	1.897	.000	1.000	72
Std. Residual	-1.892	2.687	.000	.979	72

a. Dependent Variable: Do you believe AI-assisted MRI systems improve diagnostic accuracy?


Histogram
Dependent Variable: Do you believe AI-assisted MRI systems improve diagnostic accuracy?
Mean = -2.88E-16
Std. Dev. = 0.979
N = 72
Frequency
Regression Standardized Residual


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: Do you believe AI-assisted MRI systems improve diagnostic accuracy?
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0

Scatterplot

Dependent Variable: Do you believe AI-assisted MRI systems improve diagnostic accuracy?